BST 261: Data Science II

Lecture 11

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Recurrent Neural Networks

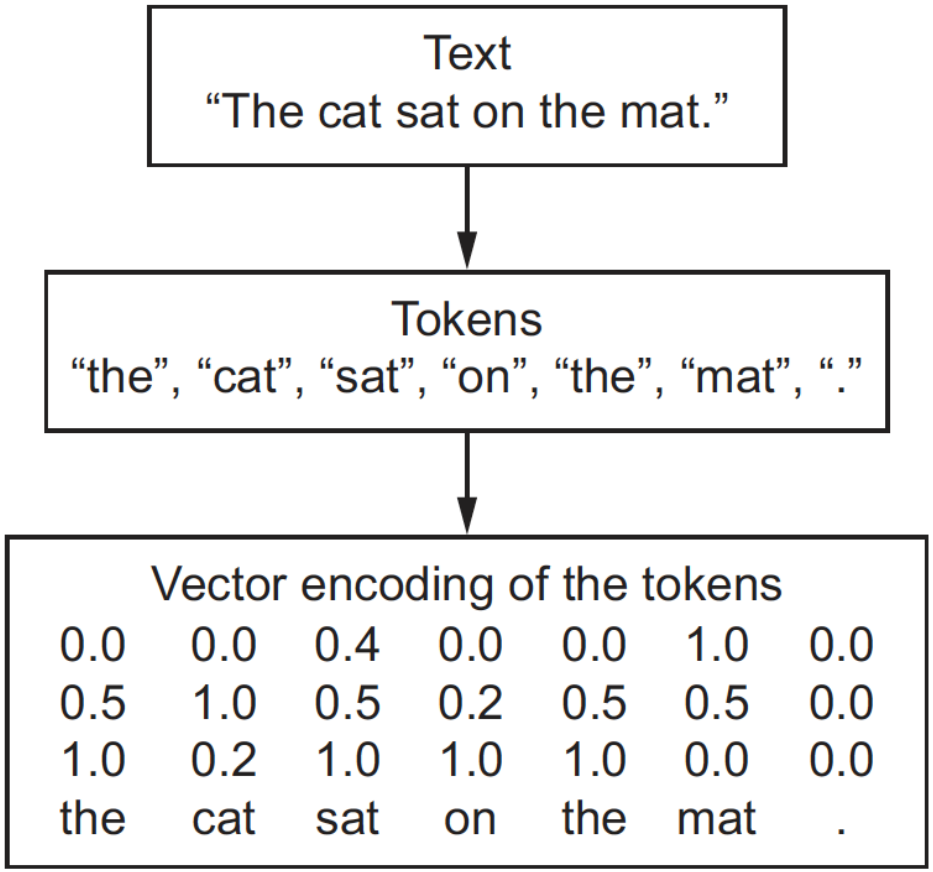
Recurrent Neural Networks

- We will now learn about deep learning models that can process text, timeseries, and sequence data in general
- The two algorithms we will cover are **recurrent neural networks** and **1D CNNs**
- Applications:
  - Document and timeseries classification e.g. identifying the topic of an article or the author of a book
  - Timeseries comparisons e.g. estimating how closely related two documents are
  - Sentiment analysis
  - Timeseries forecasting e.g. predicting weather (something that needs major improvement for Boston...)
  - Sequence-to-sequence learning e.g. decoding an English sentence into Turkish
  - Speech recognition
  - DNA sequence analysis
  - Name entity recognition
  - etc.

Text Data

- Text data can be understood as either a sequence of characters or a sequence of words
  - Most common to work at the level of words
- Like all other neural networks, we can't simply input raw text - we must **vectorize** the text: transform it into numeric tensors
- We can do this in multiple ways:
  - Segment text into words, and transform each word into a vector
  - Segment text into characters and transform each character into a vector
  - Extract n-grams (overlapping groups of multiple consecutive words or characters) of words or characters, and transform each n-gram into a vector
- The different units into which you break down text (words, characters, n-grams) are called **tokens**, and the action of breaking text into tokens is **tokenization**
- There are multiple ways to associate a vector with a token
  - One-hot encoding
  - Token embedding (or word embedding)

Tokenization and Embedding

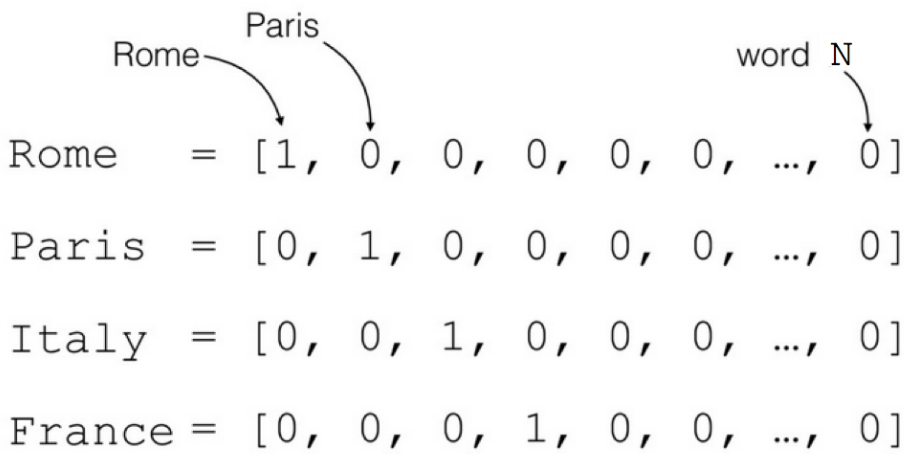


N-grams

- Word n-grams are groups of N (or fewer) consecutive words that you can extract from a sentence. The same concept may also be applied to characters instead of words.
- For example, the sentence "Data science rocks my socks off!" can be decomposed into a set of 3-grams:
  - {"Data", "Data science", "science", "science rocks", "Data science rocks", "rocks", "rocks my", "science rocks my", "my", "my socks", "socks", "rocks my socks", "off", "socks off", "my socks off"}
- This set is called a **bag of 3-grams**, which refers to the fact that it is a set of tokens, rather than a list or sequence: the tokens have no specific order
- This family of tokenization methods is called **bag-of-words**
- Order is not preserved, so the general structure of the sentence is lost
- Typically only used in **shallow** language-processing models
- Extracting n-grams is a form of feature engineering that deep learning does automatically in another way

One-hot Encoding

- Most common and most basic way to turn a token into a vector
- We used this with the IMDB and Reuters data sets
- First, associate a unique integer index with every word
- Then, turn the integer index i into a binary vector of size N (the size of the vocabulary, or number of words in the set)
- The vector is all 0s except for the ith entry, which is 1



Terminology and One-hot Encoding

Suppose we want to recognize names in a sentence:

Example sentence (x) : Marcello Pagano and Heather Mattie are writing a book.

Example output (y): [1, 1, 0, 1, 1, 0, 0, 0, 0]

$x: x^{<1>} \; x^{<2>} \; x^{<3>} \; \ldots \; x^{<9>}$

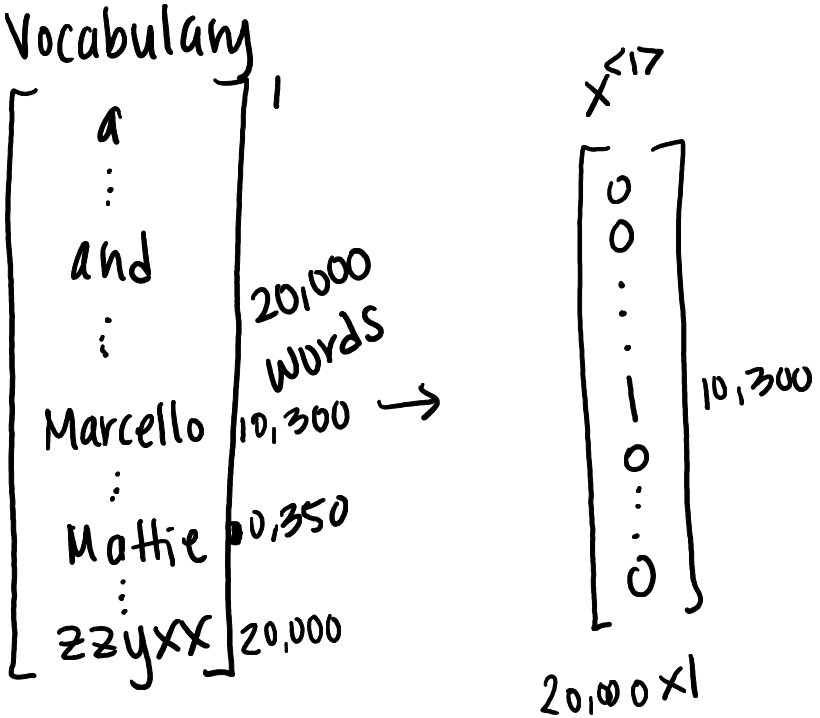
$y: y^{<1>} \; y^{<2>} \; y^{<3>} \; \ldots \; y^{<9>}$

$x^{(i)<t>}$: t^{th} element of training example i

$T_x^{(i)}$: length of sequence for training example i

ex: $T_x = 9$

$y^{(i)<t>}$, $T_y^{(i)}$



- Typically, 30,000 - 500,000 word dictionaries

One-hot Encoding in Keras

```
1  from keras.preprocessing.text import Tokenizer
2
3  samples = ['The cat sat on the mat.', 'The dog ate my homework.']
4
5  # We create a tokenizer, configured to only take
6  # into account the top-1000 most common words
7  tokenizer = Tokenizer(num_words=1000)
8  # This builds the word index
9  tokenizer.fit_on_texts(samples)
10
11 # This turns strings into lists of integer indices.
12 sequences = tokenizer.texts_to_sequences(samples)
13
14 # You could also directly get the one-hot binary representations.
15 # Note that other vectorization modes than one-hot encoding are supported!
16 one_hot_results = tokenizer.texts_to_matrix(samples, mode='binary')
17
18 # This is how you can recover the word index that was computed
19 word_index = tokenizer.word_index
20 print('Found %s unique tokens.' % len(word_index))
```

One-hot Hashing

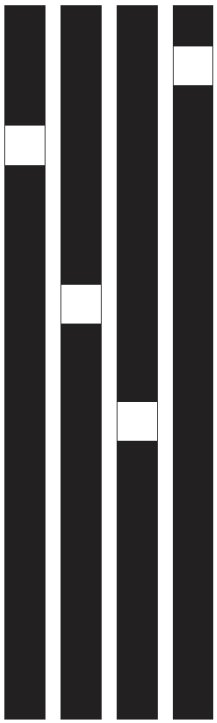
- A variant of one-hot encoding is the **one-hot hashing trick**
- Useful when the number of unique tokens is too large to handle explicitly
- Instead of explicitly assigning an index to each word and keeping a reference of these indices in a dictionary, you can hash words into vectors of fixed size
- Main advantage: saves memory and allows generation of tokens before all of the data has been seen
- Main drawback: **hash collisions**
  - Two different words end up with the same hash
  - The likelihood of this decreases when the dimensionality of the hashing space is much larger than the total number of unique tokens being hashed

One-hot Hashing

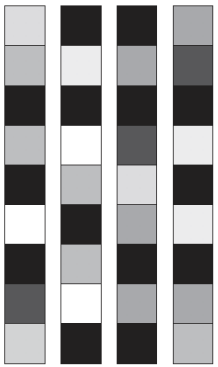
```
samples = ['The cat sat on the mat.', 'The dog ate my homework.']

# We will store our words as vectors of size 1000.
# Note that if you have close to 1000 words (or more)
# you will start seeing many hash collisions, which
# will decrease the accuracy of this encoding method.
dimensionality = 1000
max_length = 10

results = np.zeros((len(samples), max_length, dimensionality))
for i, sample in enumerate(samples):
    for j, word in list(enumerate(sample.split()))[:max_length]:
        # Hash the word into a "random" integer index
        # that is between 0 and 1000
        index = abs(hash(word)) % dimensionality
        results[i, j, index] = 1.
```

Word Embeddings

- Another common and powerful way to associate a vector with a word is the use of dense **word vectors** or **word embeddings**
- Word embeddings are dense, low-dimensional floating-point vectors
- Are learned from the data rather than hard coded
- 256, 512 and 1024-dimensional word embeddings are common



One-hot word vectors:
- Sparse
- High-dimensional
- Hardcoded



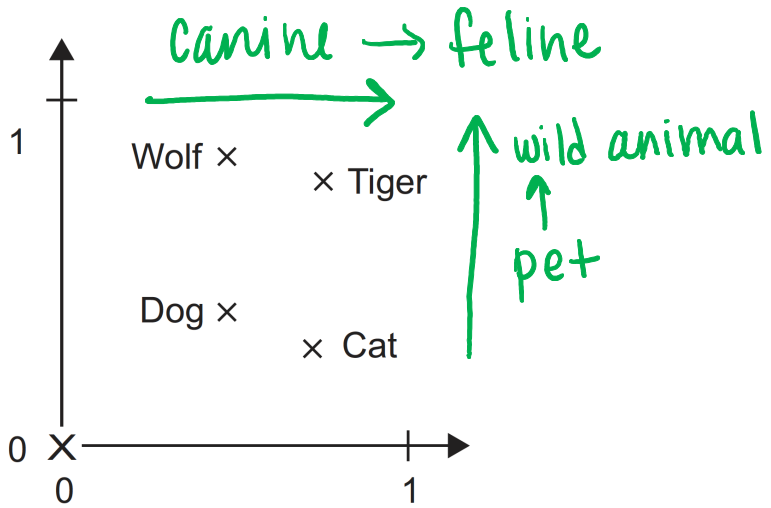
Word embeddings:
- Dense
- Lower-dimensional
- Learned from data

Word Embeddings

- There are 2 ways to obtain word embeddings:
  - Learn word embeddings jointly with the main task you care about
    - Start with random word vectors and then learn word vectors in the same way you learn the weights of the network
  - Use pre-trained word embeddings
    - Load into your model word embeddings that were precomputed using a different machine-learning task than the one you're trying to solve

Learning Word Embeddings

- It's easy to simply associate a vector with a word randomly - but this results in an embedding space without structure, and things like synonyms that could be interchangeable will have completely different embeddings
- This makes it difficult for a deep neural network to make sense of these representations
- It is better for similar words to have similar embeddings, and dissimilar words to have dissimilar embeddings
  - We can, for example, relate the L2 distance to the similarity of the words with a smaller distance meaning the words are similar and bigger distances indicating very different words



Word Embeddings

- Common examples of useful geometric transformations are “sex" and “plural" vectors:
  - Adding a “female" vector to the vector “king" will result in the vector “queen"
  - Adding the “plural" vector to the vector “elephant" will result in the vector “elephants"
- Is there a word-embedding space that would perfectly map human language and be used in any natural-language processing task?
  - Maybe, but we haven’t discovered it yet
  - Very complicated - many different languages that are not isomorphic due to specific cultures and contexts
  - A “good" word-embedding space depends on the task

The Embedding Layer

- Keras has a function that enables learning word-embeddings: the `embedding` **layer**
- Basically a dictionary that maps integer indices (that represent words) to dense vectors
- It takes integers as input, looks up the integers in an internal dictionary, and returns the associated vectors

$$\text{Word index} \rightarrow \text{Embedding layer} \rightarrow \text{Corresponding word vector}$$

- Input: 2D tensor of integers of shape (`samples`, `sequence_length`)
- Note that you need to select a sequence length that is the same for all sequences
  - If a sequence is shorter than the set `sequence_length`, pad the remaining entries with 0s
  - If a sequence is longer than the set `sequence_length`, truncate the sequence

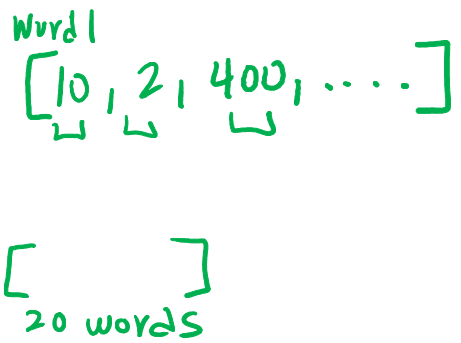
```
1 from keras.layers import Embedding
2 embedding_layer = Embedding(1000, 64)
```

- The `embedding` layer returns a 3D tensor of shape (`samples`, `sequence_length`, `embedding_dimensionality`)

IMDB Example

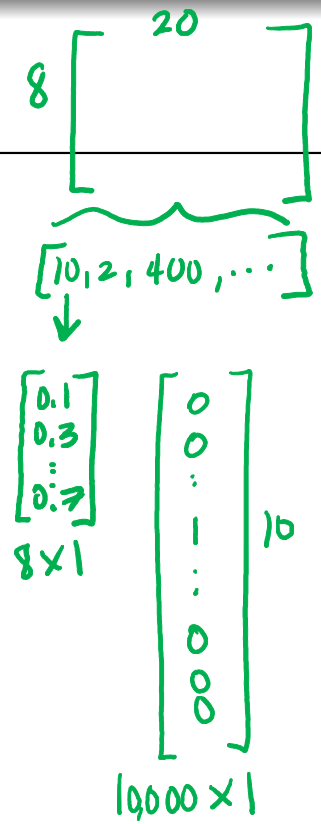
- Recall the IMDB movie review sentiment prediction task from an earlier lecture
- We have thousands of reviews and we want to classify them as either positive or negative

```
1  from keras.datasets import imdb
2  from keras import preprocessing
3
4  # Number of words to consider as features
5  max_features = 10000
6  # Cut texts after this number of words
7  # (among top max_features most common words)
8  maxlen = 20
9
10 # Load the data as lists of integers.
11 (x_train, y_train), (x_test, y_test) = imdb.load_data(num_words=max_features)
12
13 # This turns our lists of integers
14 # into a 2D integer tensor of shape `(samples, maxlen)`
15 x_train = preprocessing.sequence.pad_sequences(x_train, maxlen=maxlen)
16 x_test = preprocessing.sequence.pad_sequences(x_test, maxlen=maxlen)
```



IMDB Example

```
1  from keras.models import Sequential
2  from keras.layers import Flatten, Dense
3
4  model = Sequential()
5  # We specify the maximum input length to our Embedding layer
6  # so we can later flatten the embedded inputs
7  model.add(Embedding(10000, 8, input_length=maxlen))
8  # After the Embedding layer,
9  # our activations have shape `(samples, maxlen, 8)`.
10
11 # We flatten the 3D tensor of embeddings
12 # into a 2D tensor of shape `(samples, maxlen * 8)`
13 model.add(Flatten())
14
15 # We add the classifier on top
16 model.add(Dense(1, activation='sigmoid'))
17 model.compile(optimizer='rmsprop', loss='binary_crossentropy', metrics=['acc'])
18 model.summary()
19
20 history = model.fit(x_train, y_train,
21                     epochs=10,
22                     batch_size=32,
23                     validation_split=0.2)
```



8 x 20 matrix → 20 · 8 vector

IMDB Example

- This simple model reaches an accuracy of approximately 76%
- Note that this model treats each word in the input sequence separately, without considering inter-word relationships and sentence structure
- For example, the following two reviews might both be classified as positive:
  - “The cast was absolutely spectacular. "
  - “This was a spectacular waste of my time."
- We need to add recurrent layers or 1D convolutional layers on top of the embedded sequences in order to take into account the sequence as a whole

Using pre-trained Word Embeddings

- Similar to using pre-trained convolutional bases, we can use pre-trained word embeddings
- Particularly useful when your sample size is small
- Load embedding vectors from a precomputed embedding space that is highly structured with useful properties
  - Captures generic aspects of language structure
- These embeddings are typically computed using word-occurrence statistics: observations about what words co-occur in sentences or documents
- Various word-embedding methods exist:
  - **Word2vec** algorithm (developed by Tomas Mikolov at Google in 2013)
  - **GloVe**: Global Vectors for Word Representation (developed by researchers at Stanford in 2014)
- Both embeddings can be used in Keras

IMDB Example

- This time we will download the original text data and use pre-trained word embeddings
- You can download the data from `http://ai.stanford.edu/~amaas/data/sentiment/`

```
1  import os
2
3  imdb_dir = '/home/ubuntu/data/aclImdb'
4  train_dir = os.path.join(imdb_dir, 'train')
5
6  labels = []
7  texts = []
8
9  for label_type in ['neg', 'pos']:
10     dir_name = os.path.join(train_dir, label_type)
11     for fname in os.listdir(dir_name):
12         if fname[-4:] == '.txt':
13             f = open(os.path.join(dir_name, fname))
14             texts.append(f.read())
15             f.close()
16             if label_type == 'neg':
17                 labels.append(0)
18             else:
19                 labels.append(1)
```

IMDB Example

```
from keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences
import numpy as np

maxlen = 100  # We will cut reviews after 100 words
training_samples = 200  # We will be training on 200 samples
validation_samples = 10000  # We will be validating on 10000 samples
max_words = 10000  # We will only consider the top 10,000 words in the dataset

tokenizer = Tokenizer(num_words=max_words)
tokenizer.fit_on_texts(texts)
sequences = tokenizer.texts_to_sequences(texts)

word_index = tokenizer.word_index
print('Found %s unique tokens.' % len(word_index))

data = pad_sequences(sequences, maxlen=maxlen)

labels = np.asarray(labels)
print('Shape of data tensor:', data.shape)
print('Shape of label tensor:', labels.shape)

Found 88582 unique tokens.
Shape of data tensor: (25000, 100)
Shape of label tensor: (25000,)
```

IMDB Example

```
# Split the data into a training set and a validation set
# But first, shuffle the data, since we started from data
# where sample are ordered (all negative first, then all positive).
indices = np.arange(data.shape[0])
np.random.shuffle(indices)
data = data[indices]
labels = labels[indices]

x_train = data[:training_samples]
y_train = labels[:training_samples]
x_val = data[training_samples: training_samples + validation_samples]
y_val = labels[training_samples: training_samples + validation_samples]
```

IMDB Example

- Download the GloVe pre-computed word embeddings from 2014 English Wikipedia from `https://nlp.stanford.edu/projects/glove/`
- It contains 100-dimensional embedding vectors for 400,000 words (or non-word tokens)

```
glove_dir = '/home/ubuntu/data/'

embeddings_index = {}
f = open(os.path.join(glove_dir, 'glove.6B.100d.txt'))
for line in f:
    values = line.split()
    word = values[0]
    coefs = np.asarray(values[1:], dtype='float32')
    embeddings_index[word] = coefs
f.close()

print('Found %s word vectors.' % len(embeddings_index))
Found 400000 word vectors.
```

IMDB Example

- Now build an embedding matrix that we will be able to load into an `Embedding` layer
- Needs to be of shape (`max_words`, `embedding_dim`), where each entry i contains the `embedding_dim`-dimensional vector for the word of index i in the reference word index

```
embedding_dim = 100

embedding_matrix = np.zeros((max_words, embedding_dim))
for word, i in word_index.items():
    embedding_vector = embeddings_index.get(word)
    if i < max_words:
        if embedding_vector is not None:
            # Words not found in embedding index will be all-zeros.
            embedding_matrix[i] = embedding_vector
```

IMDB Example

- Now build a model with the same architecture as before

```
from keras.models import Sequential
from keras.layers import Embedding, Flatten, Dense

model = Sequential()
model.add(Embedding(max_words, embedding_dim, input_length=maxlen))
model.add(Flatten())
model.add(Dense(32, activation='relu'))
model.add(Dense(1, activation='sigmoid'))
```

- Load the GloVe embeddings in the model

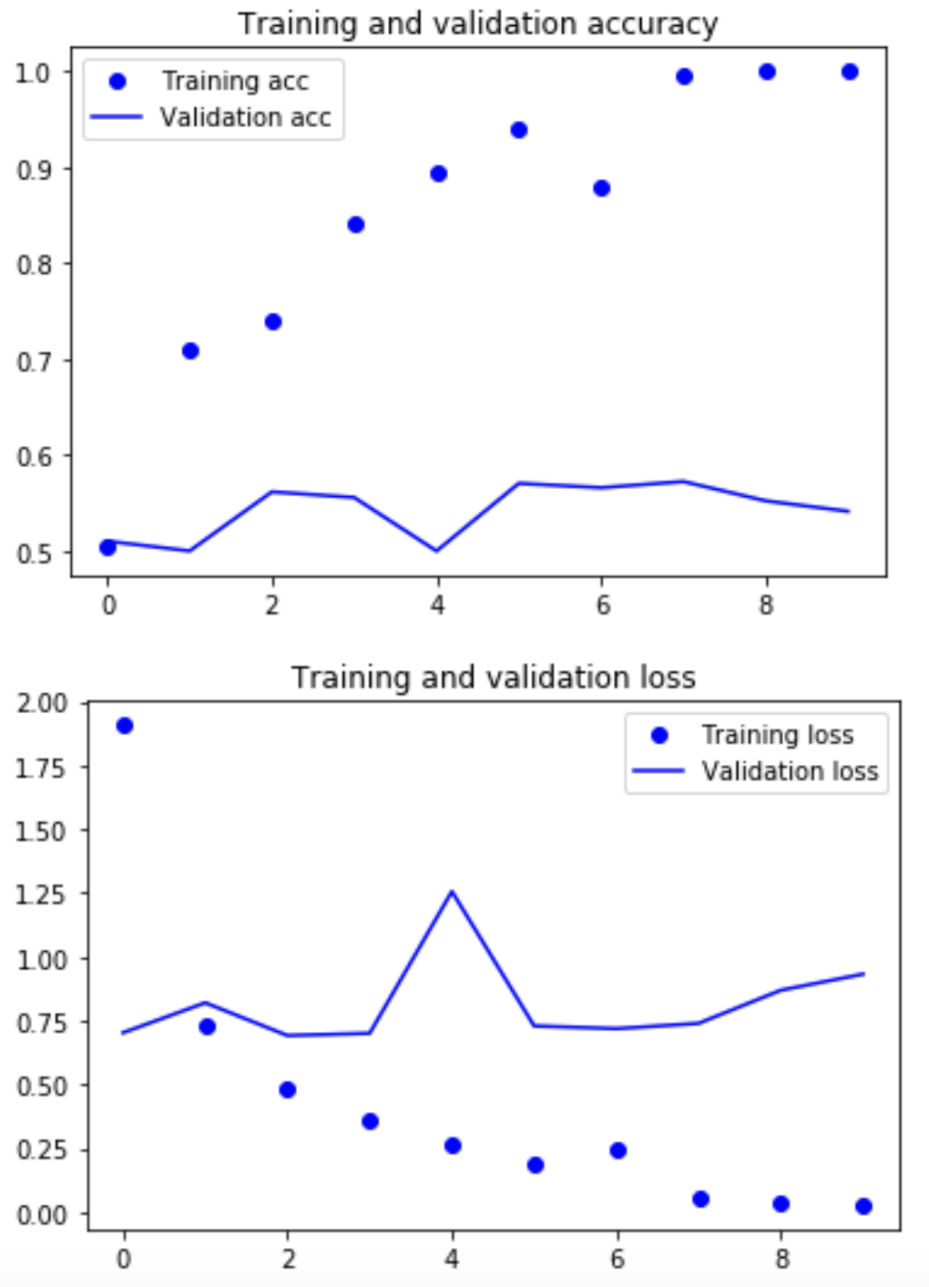
```
model.layers[0].set_weights([embedding_matrix])
model.layers[0].trainable = False
```

IMDB Example

- Train and evaluate

```
1
2 model.compile(optimizer='rmsprop',
3               loss='binary_crossentropy',
4               metrics=['acc'])
5 history = model.fit(x_train, y_train,
6                     epochs=10,
7                     batch_size=32,
8                     validation_data=(x_val, y_val))
9 model.save_weights('pre_trained_glove_model.h5')
```

IMDB Example

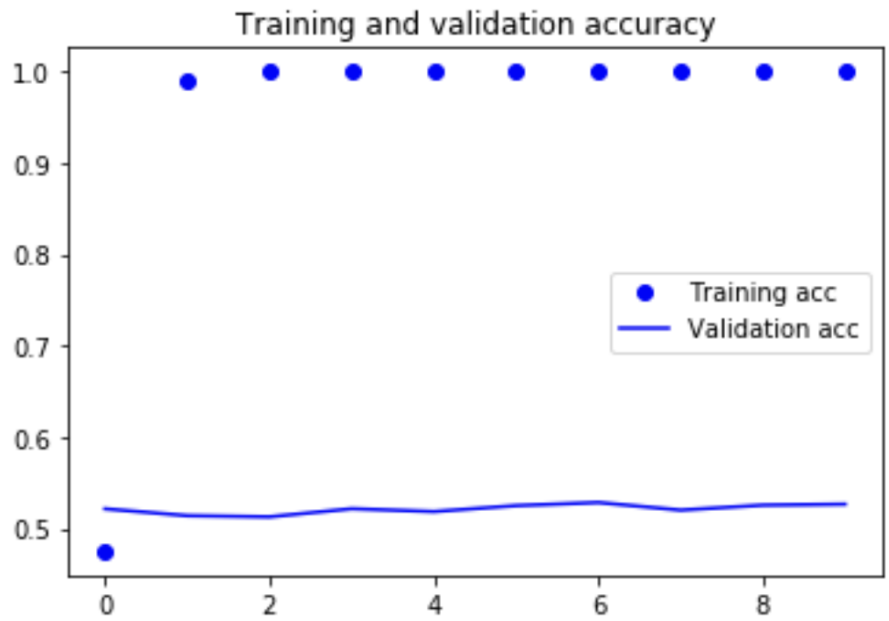


IMDB Example

- Now let's see what happens when we train the same model without loading the pre-trained word embeddings and without freezing the embedding layer
- Here, we are learning a task-specific embedding of our input tokens
- This is generally more powerful than pre-trained word embeddings, but only when a lot of data is available

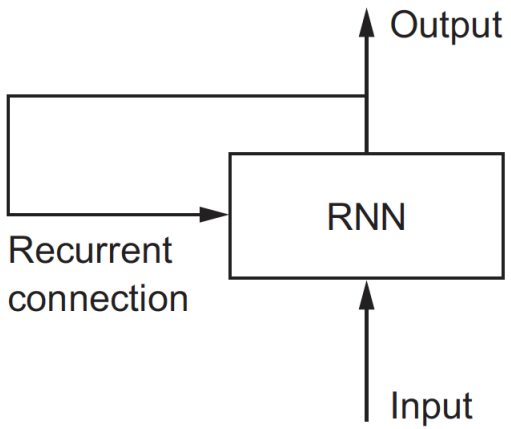
```
from keras.models import Sequential
from keras.layers import Embedding, Flatten, Dense

model = Sequential()
model.add(Embedding(max_words, embedding_dim, input_length=maxlen))
model.add(Flatten())
model.add(Dense(32, activation='relu'))
model.add(Dense(1, activation='sigmoid'))

model.compile(optimizer='rmsprop',
              loss='binary_crossentropy',
              metrics=['acc'])
history = model.fit(x_train, y_train,
                    epochs=10,
                    batch_size=32,
                    validation_data=(x_val, y_val))
```

IMDB Example



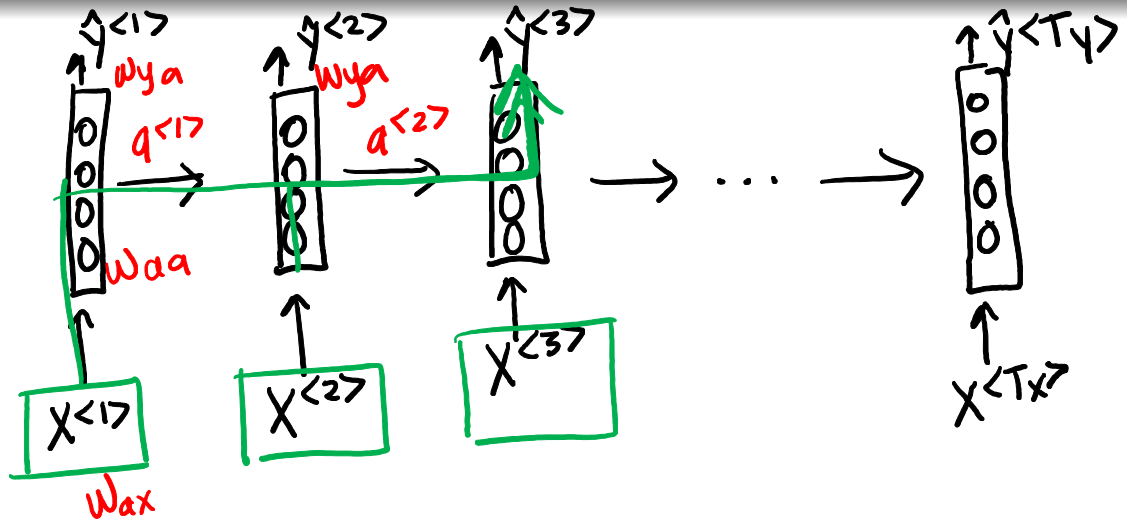
RNNs

- When we were studying deep feedforward networks and CNNs, each input was processed independently and no "state" was kept between examples
- When reading text data, we process it word by word, keeping memories of what came before and eventually discovering the meaning of the whole sentence
- This "memory" property is the main difference between feedforward networks and CNNs, which are memoryless
- RNNs process sequences by iterating through the sequence elements and maintaining a **state** containing the information relative to what it has seen so far
  - Some like to think of it as a network with an internal loop



- The state of the RNN is reset between processing two different, independent sequences (examples), so you can still think of each sequence as a single data point, but that each data point is processed with an internal loop rather than in a single step

RNN Models: "Many-to-many" with $T_x = T_y$



"unrolled" schematic of RNN

* parameters are shared
* weakness: only uses info from earier in sequence

→ BRNNs (bi-directional RNNs)

from previous timestep

$$a^{<t>} = g(W_{aa} a^{<t-1>} + W_{ax} x^{<t>} + b)$$

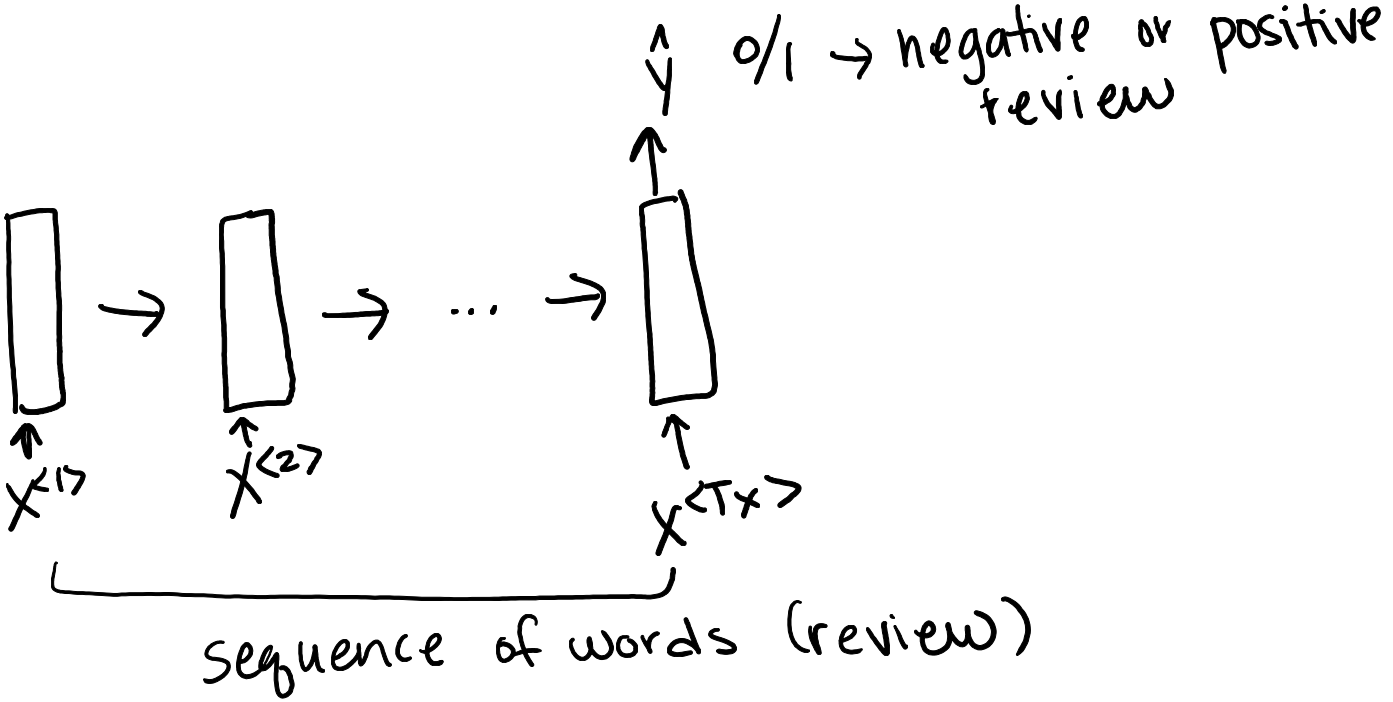
$$\hat{y}^{<t>} = h(W_{ya} a^{<t>} + b_y)$$

$g(\cdot)$: relu, tanh

$h(\cdot)$: sigmoid, softmax

depends on task

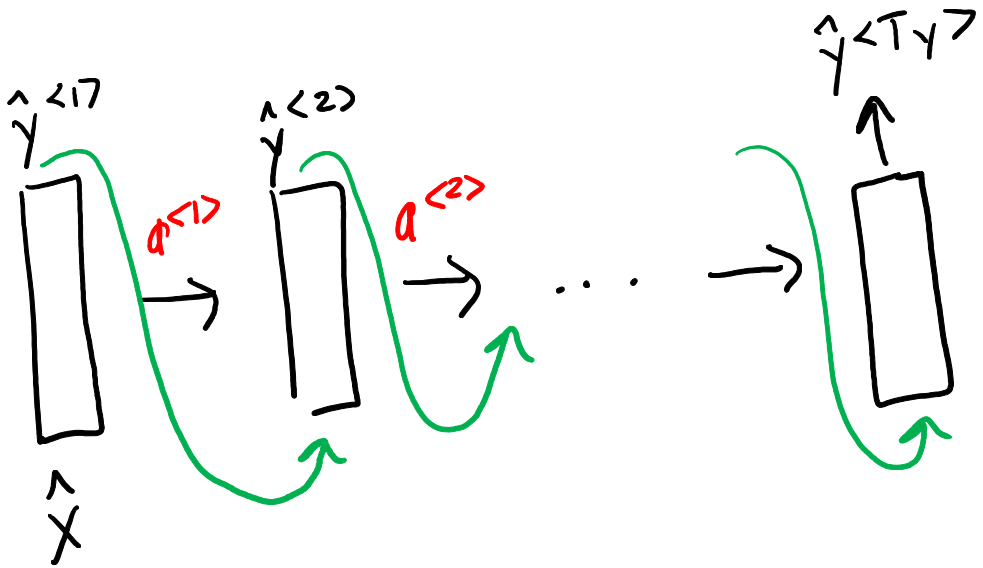
RNN Models: “Many-to-one"



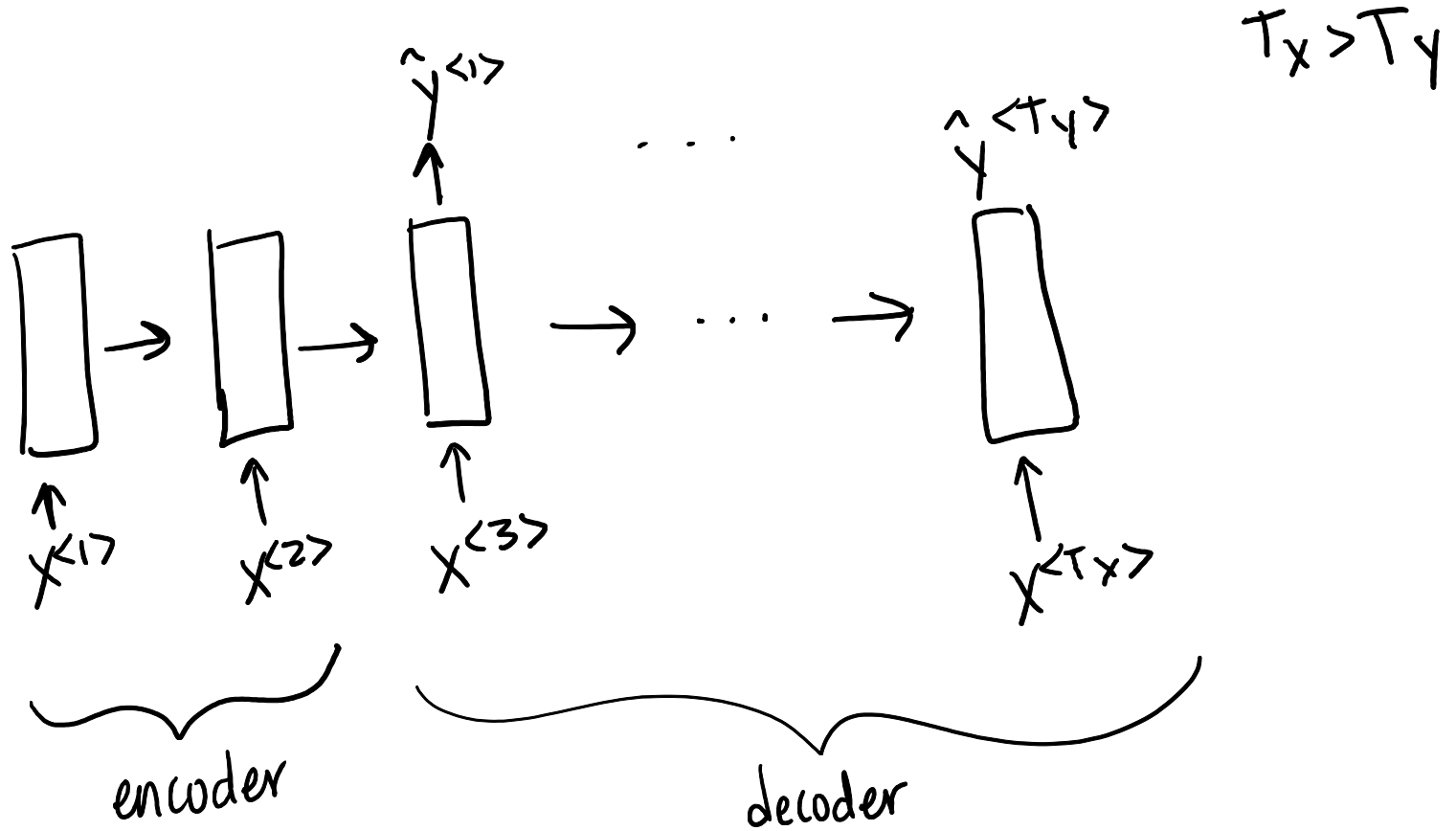
RNN Models: “One-to-many"

$x \rightarrow y^{<1>}\ y^{<2>}\ y^{<3>} \ldots y^{<T_y>}$

- music generation



RNN Models: “Many-to-many" with $T_x \neq T_y$



- Note that the time step index need not literally refer to the passage of time in the real world - it refers only to the position in the sequence.
- Recurrent networks share parameters in a different way than what we saw with CNNs
- Each member of the output is a function of the previous members of the output
- Each member of the output is produced using the same update rule applied to the previous outputs
- This recurrent formulation results in the sharing of parameters through a very deep computational graph

$$\boldsymbol{h}^{<t>} = f(\boldsymbol{h}^{(<t-1>}, \boldsymbol{x}^{<t>}; \boldsymbol{w}) \tag{1}$$

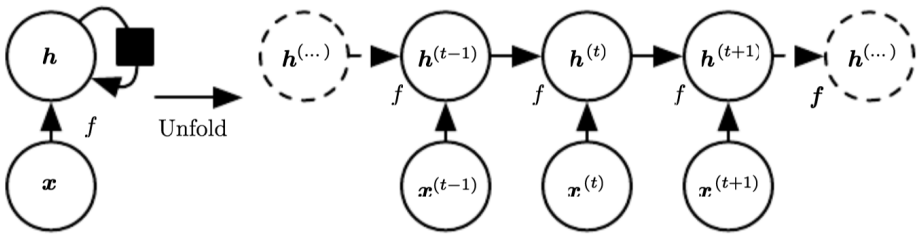
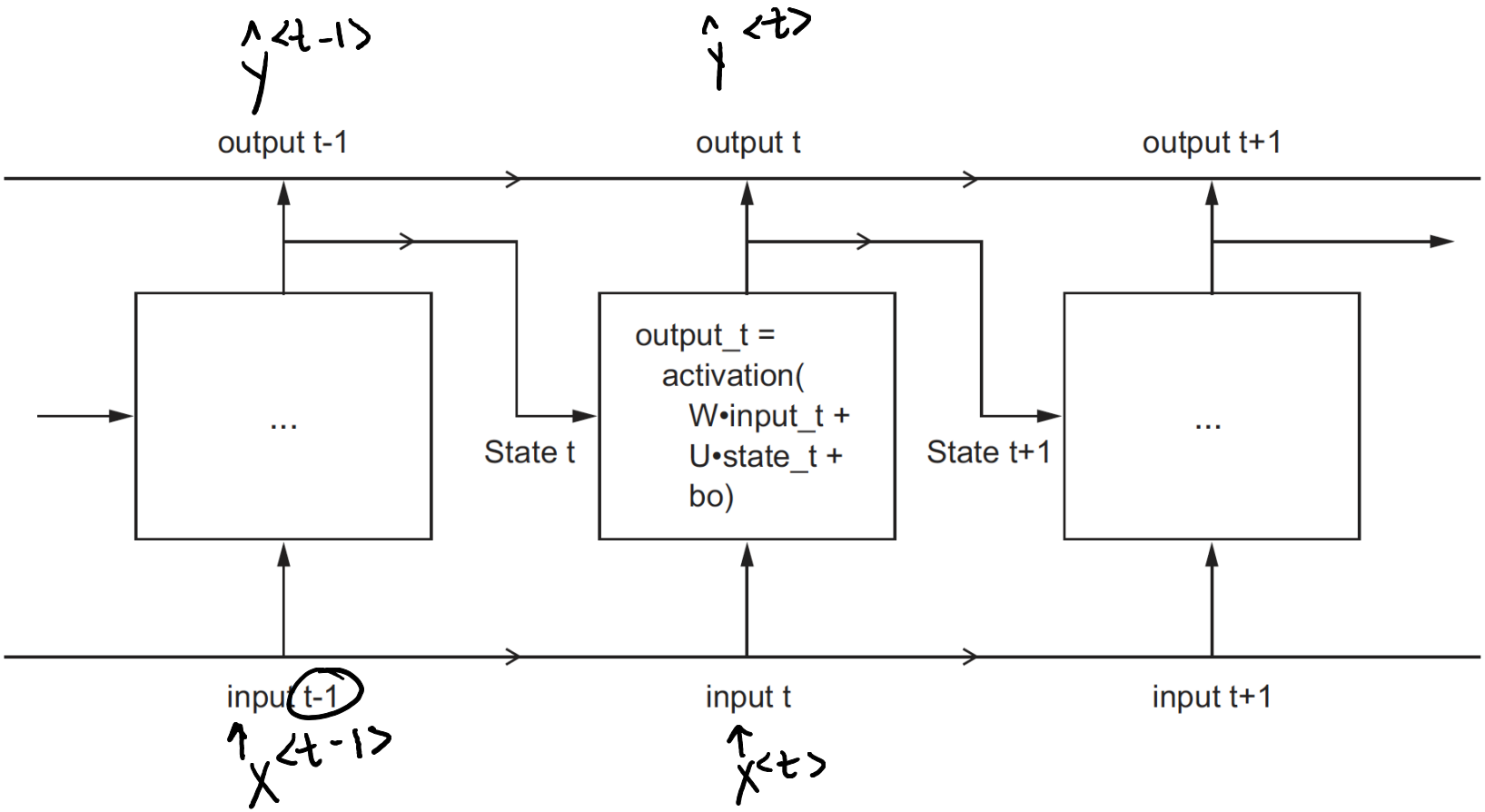


Figure 10.2: A recurrent network with no outputs. This recurrent network just processes information from the input $\boldsymbol{x}$ by incorporating it into the state $\boldsymbol{h}$ that is passed forward through time. *(Left)* Circuit diagram. The black square indicates a delay of a single time step. *(Right)* The same network seen as an unfolded computational graph, where each node is now associated with one particular time instance.

Unfolded RNN



RNN Forward Pass

- For better intuition, we can write how a training example is fed through an RNN with the following code

1 example

```
import numpy as np
timesteps = 100              # Number of timesteps in the input sequence
input_features = 32         # Dimensionality of the input feature shape
output_features = 64      # Dimensionality of the output feature shape

# Input random data just as an example
inputs = np.random.random((timesteps, input_features))
# Initial state: a zero vector
state_t = np.zeros((output_features, ))

# Create random weight matrices
W = U = np.random.random((output_features, input_features))
U = np.random.random((output_features, output_features))
b = np.random.random((output_features, ))

successive_outputs = []
for input_t in inputs:
    # Combines the input with the current state (the previous output) to obtain
        the current output
    output_t = np.tanh(np.dot(W, input_t) + np.dot(U, state_t) + b)
    # Stores the output in a list
    sucessive_outputs.append(output_t)
    # Updates the state of the network for the next time step
    state_t = output_t

# The final output is a 2D tensor of shape (timesteps, output_features)
final_output_sequence = np.concatenate(successive_outputs, axis = 0)
```

Simple RNN Layer

- The `SimpleRNN` processes batches of of sequences
- Takes as input a 3D tensor of shape (`batch_size`, `timesteps`, `input_features`)
- The output can return either the full sequence of successive outputs for each timestep, or only the last output for each input sequence
  - This is controlled by the `return_sequences` argument
- Only the last timestep:

```
1 from keras.models import Sequential
2 from keras.layers import Embedding, SimpleRNN
3
4 model = Sequential()
5 model.add(Embedding(10000, 32))
6 model.add(SimpleRNN(32))
```

- The full state sequence:

```
1 model = Sequential()
2 model.add(Embedding(10000, 32))
3 model.add(SimpleRNN(32, return_sequences=True))
```

Simple RNN

- It can be useful to stack several recurrent layers in order to increase the representational power of the network
- All of the intermediate layers must return full sequence outputs:

```
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))  # This last layer only returns the last outputs.
```

IMDB Example with SimpleRNN

- Preprocess the data

```
1  from keras.datasets import imdb
2  from keras.preprocessing import sequence
3
4  max_features = 10000  # number of words to consider as features
5  maxlen = 500  # cut texts after this number of words (among top max_features
       most common words)
6  batch_size = 32
7
8  print('Loading data...')
9  (input_train, y_train), (input_test, y_test) = imdb.load_data(num_words=
       max_features)
10 print(len(input_train), 'train sequences')
11 print(len(input_test), 'test sequences')
12
13 print('Pad sequences (samples x time)')
14 input_train = sequence.pad_sequences(input_train, maxlen=maxlen)
15 input_test = sequence.pad_sequences(input_test, maxlen=maxlen)
16 print('input_train shape:', input_train.shape)
17 print('input_test shape:', input_test.shape)
18
19 Loading data...
20 25000 train sequences
21 25000 test sequences
22 Pad sequences (samples x time)
23 input_train shape: (25000, 500)
24 input_test shape: (25000, 500)
```

IMDB Example with SimpleRNN

- Train the model

```
from keras.layers import Dense

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

model.compile(optimizer='rmsprop', loss='binary_crossentropy', metrics=['acc'])
history = model.fit(input_train, y_train,
                    epochs=10,
                    batch_size=128,
                    validation_split=0.2)
```

IMDB Example with SimpleRNN

- The simple RNN performs worse than the feedforward network we used earlier in the course
  - Here we only consider the first 500 words and not the entire sequences
  - `SimpleRNN` isn't great at processing long sequences such as text