EDAN95
Applied Machine Learning
http://cs.lth.se/edan95/
Lecture 9: Autoencoders and Generative Learning

Pierre Nugues

Lund University
Pierre.Nugues@cs.lth.se
http://cs.lth.se/pierre_nugues/

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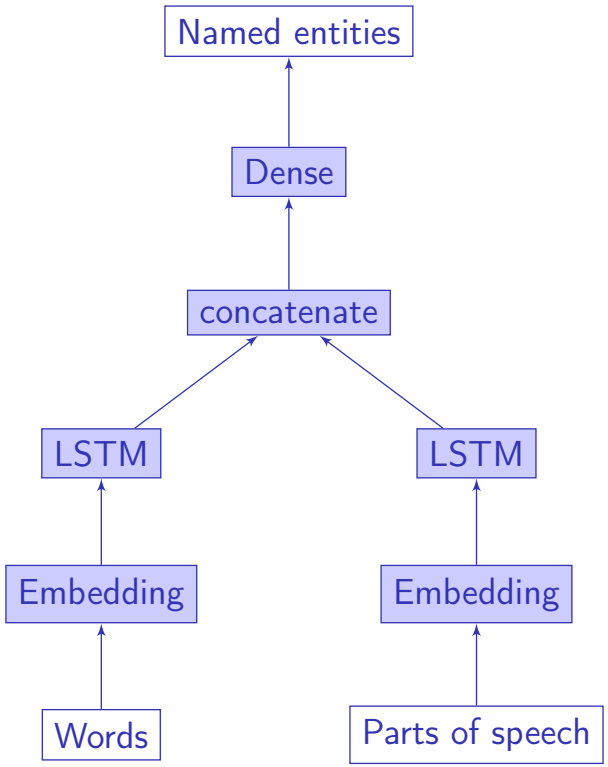
The Functional Model

So far, we have used the `Sequential` model to build networks
These models correspond to pipelines with one input and one output



To build graphs, we need to use the functional model.

Comparing the Models

Sequential:

```
seq_model = Sequential()
seq_model.add(layers.Dense(32, activation='relu',
  input_shape=(64,)))
seq_model.add(layers.Dense(32, activation='relu'))
seq_model.add(layers.Dense(10, activation='softmax'))
```

Functional:

```
input_tensor = Input(shape=(64,))
x = layers.Dense(32, activation='relu')(input_tensor)
x = layers.Dense(32, activation='relu')(x)
output_tensor = layers.Dense(10, activation='softmax')(x)
model = Model(input_tensor, output_tensor)
```

From Chollet, page 237

Building a Multi Input Model

To build a multi input, we need the functional model and at a certain point, merge the branches with `layers.concatenate()` function
We will now build a NER tagger that uses two inputs: the words and parts of speech

The Word Branch

```
text_vocabulary_size = len(word_set) + 2
text_input = Input(shape=(None,), dtype='int32', name='text')
embedded_text = layers.Embedding(text_vocabulary_size,
                                 64, mask_zero=True)(text_input)
encoded_text = layers.LSTM(32,
                           return_sequences=True)(embedded_text)
```

The Part-of-Speech Branch

```
pos_vocabulary_size = len(pos_set) + 2
pos_input = Input(shape=(None,),
                  dtype='int32',
                  name='pos')
embedded_pos = layers.Embedding(pos_vocabulary_size,
                                32, mask_zero=True)(pos_input)
encoded_pos = layers.LSTM(16,
                  return_sequences=True)(embedded_pos)
```

Merging and Common Part

```
concatenated = layers.concatenate(
            [encoded_text, encoded_pos],axis=-1)
ner_vocabulary_size = len(ner_set) + 2
ner = layers.Dense(ner_vocabulary_size,
                   activation='softmax')(concatenated)

model = Model([text_input, pos_input], ner)
model.compile(optimizer='rmsprop',
              loss='categorical_crossentropy',
              metrics=['acc'])
```

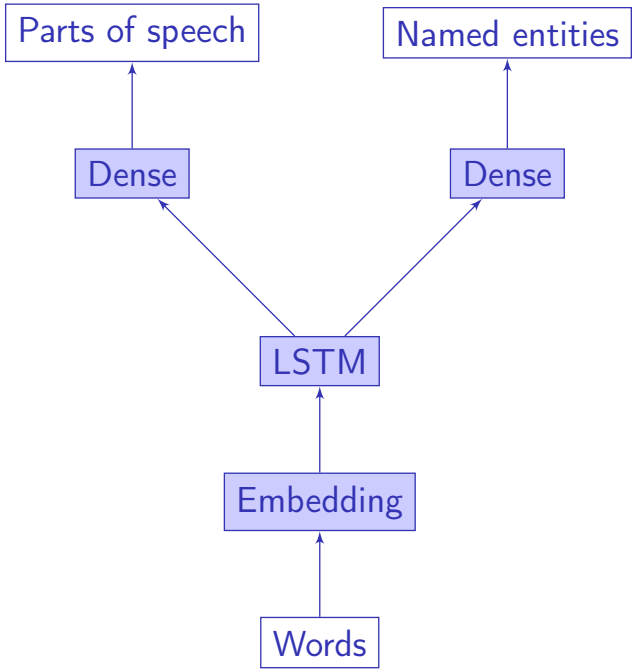
Code Example

The NER tagger with two inputs: the words and parts of speech and we will compare it to a sequential model

Jupyter Notebooks: `5.2-multiinput.ipynb` and `5.3-monoinput.ipynb`

Multiple Outputs

It is also possible to build a model with multiple outputs, for instance the word as input to predict the parts of speech and the named entities.



The Word Input

```
text_vocabulary_size = len(word_set) + 2
text_input = Input(shape=(None,), dtype='int32', name='text')
embedded_text = layers.Embedding(text_vocabulary_size,
                                 64, mask_zero=True)(text_input)
encoded_text = layers.LSTM(32,
                           return_sequences=True)(embedded_text)
```

The POS output

```
pos_vocabulary_size = len(pos_set) + 2
pos_output = layers.Dense(pos_vocabulary_size,
                          activation='softmax',
                   name='pos')(encoded_text)
```

The NER Output

```
ner_vocabulary_size = len(ner_set) + 2
ner_output = layers.Dense(ner_vocabulary_size,
                          activation='softmax',
                          name='ner')(encoded_text)
```

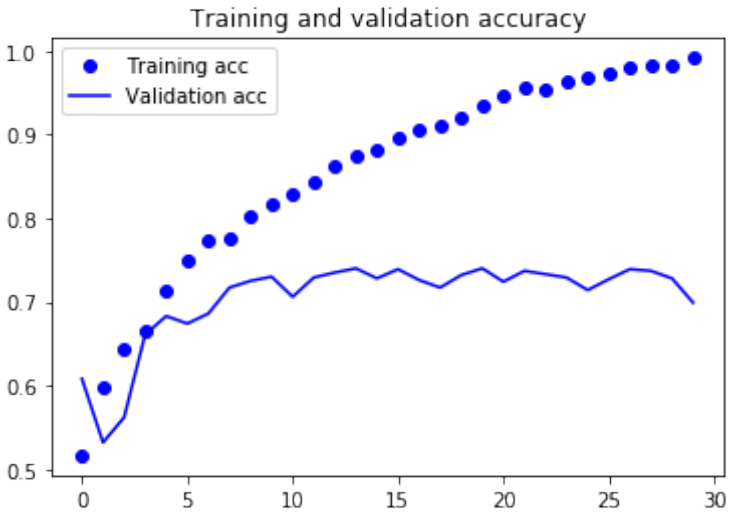
The Model

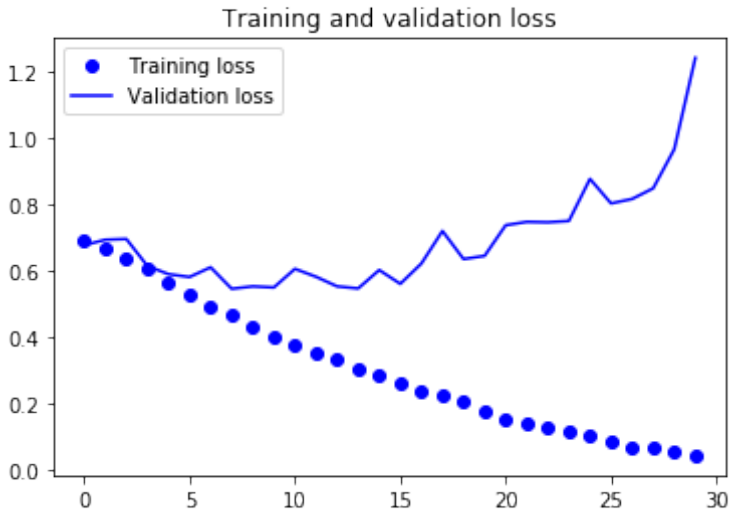
```
model = Model(text_input, [pos_output, ner_output])
model.compile(optimizer='rmsprop',
              loss=['categorical_crossentropy',
                    'categorical_crossentropy'],
              metrics=['acc'])

model.fit(X_words_idx,
          {'pos':Y_pos_idx_cat, 'ner':Y_ner_idx_cat},
          epochs=3, batch_size=128)
```

It is possible to build mode complex models, provided that they have the form of a directed acyclic graph. See the book.

Monitoring Training

We have seen different shapes of validation accuracies and loss:





15 epochs seem the optimal number and it is probably useless to run more. Keras provided callbacks for this.

Two Callbacks

1. `keras.callbacks.EarlyStopping` to stop training when validation scores do not improve;
2. `keras.callbacks.ModelCheckpoint` to save models

```
callbacks_list = [
    keras.callbacks.EarlyStopping(
        monitor='acc',
        patience=1,),
    keras.callbacks.ModelCheckpoint(
        filepath='my_model.h5',
        monitor='val_loss',
        save_best_only=True,)
 ]
```

From Chollet, page 250

Including the Callbacks

```
model.compile(optimizer='rmsprop',
              loss='binary_crossentropy',
              metrics=['acc'])
model.fit(x, y,
          epochs=10,
          batch_size=32,
          callbacks=callbacks_list,
          validation_data=(x_val, y_val))
```

You can also write your own callbacks, see Chollet, page 251-252

Tensorboard

Tensorboard is a visualization tool
You include it with a callback

```
callbacks = [
    keras.callbacks.TensorBoard(
        log_dir='tb_log_folder',
        histogram_freq=1
) ]
```

Demonstration

Tensorboard

Generative Learning

Words and characters have specific contexts of use.
Pairs of words like *strong* and *tea* or *powerful* and *computer* are not random associations.
Psychological linguistics tells us that it is difficult to make a difference between *writer* and *rider* without context
A listener will discard the improbable *rider of books* and prefer *writer of books*
A language model is the statistical estimate of a word sequence.
Originally developed for speech recognition
The language model component enables to predict the next word given a sequence of previous words

N-Grams

The types are the distinct words of a text while the tokens are all the words or symbols.
The phrases from *Nineteen Eighty-Four*

> *War is peace*
> *Freedom is slavery*
> *Ignorance is strength*

have 9 tokens and 7 types.
Unigrams are single words
Bigrams are sequences of two words
Trigrams are sequences of three words

Trigrams

Word	Rank	More likely alternatives
We	9	*The This One Two A Three Please In*
need	7	*are will the would also do*
to	1	
resolve	85	*have know do...*
all	9	*the this these problems...*
of	2	*the*
the	1	
important	657	*document question first...*
issues	14	*thing point to...*
within	74	*to of and in that...*
the	1	
next	2	*company*
two	5	*page exhibit meeting day*
days	5	*weeks years pages months*

Language Models and Generation

Using a n-gram language model, we can generate a sequence of words.
Starting from a first word, w_1, we extract the conditional probabilities: $P(w_2|w_1)$.
We could take the highest value, but it would always generate the same sequence.
Instead, we will draw our words from a multinomial distribution using `np.random.multinomial()`.
Given a probability distribution, this function draws a sample that complies the distribution.
Having, $P(want|I) = 0.5$, $P(wish|I) = 0.3$, $P(will|I) = 0.2$, the function will draw wish 30% of the time.

Code Example

Generating sequences with Bayesian probabilities
Jupyter Notebooks: `5.7-generation.ipynb`

Generating Character Sequences with LSTMs

In the previous example, we used words. We can use characters instead.
We also used Bayesian probabilities. We can use LSTMs instead.
This is the idea of Chollet's program, pages 272-278.
X consists of sequences of 60 characters with a step of 3 characters
y is the character following the sequence
Let us use this excerpt:

is there not ground for suspecting that all philosophers

and 10 characters, where ␣ marks a space:

$$\mathbf{X} = \begin{bmatrix} \text{i} & \text{s} & \text{␣} & \text{t} & \text{h} & \text{e} & \text{r} & \text{e} & \text{␣} & \text{n} \\ \text{t} & \text{h} & \text{e} & \text{r} & \text{e} & \text{␣} & \text{n} & \text{o} & \text{t} & \text{␣} \\ \text{r} & \text{e} & \text{␣} & \text{n} & \text{o} & \text{t} & \text{␣} & \text{g} & \text{r} & \text{o} \\ \text{n} & \text{o} & \text{t} & \text{␣} & \text{g} & \text{r} & \text{o} & \text{u} & \text{n} & \text{d} \\ \text{␣} & \text{g} & \text{r} & \text{o} & \text{u} & \text{n} & \text{d} & \text{␣} & \text{f} & \text{o} \end{bmatrix}; \mathbf{y} = \begin{bmatrix} \text{o} \\ \text{g} \\ \text{u} \\ \text{␣} \\ \text{r} \end{bmatrix}$$

Generating Character Sequences with LSTMs

In addition, Chollet uses a "temperature" function to transform the probability distribution: sharpen or damps it.

```
def sample(preds, temperature=1.0):
    preds = np.asarray(preds).astype('float64')
    preds = np.log(preds) / temperature
    exp_preds = np.exp(preds)
    preds = exp_preds / np.sum(exp_preds)
    probas = np.random.multinomial(1, preds, 1)
    return np.argmax(probas)
```

with the input `[0.2, 0.5, 0.3]`, we obtain:

- Temperature = 2, `[0.26275107 0.41544591 0.32180302]`
- Temperature = 1, `[0.2 0.5 0.3]`
- Temperature = 0.5 `[0.10526316 0.65789474 0.23684211]`
- Temperature = 0.2 `[0.00941176 0.91911765 0.07147059]`

Code Example

Form Chollet's github repository:
Jupyter Notebooks: `8.1-text-generation-with-lstm.ipynb`

Sequence-to-Sequence Translation

https://blog.keras.io/a-ten-minute-introduction-to-sequence-to-sequence-learning-in-html

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