EDAN95 Applied Machine Learning

Lecture 8: Generative Learning and Encoders-Decoders

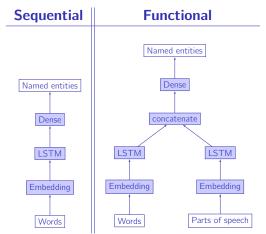
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The Functional Model

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.

Building the Models

For a pipeline, the structure is nearly the same, with different Keras classes:

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

Example of a Multi Input Model: Named Entity Recognition

CoNLL 2003							
Words	PPOS	PGroups	Named entities				
U.N.	NNP	I-NP	I-ORG				
official	NN	I-NP	0				
Ekeus	NNP	I-NP	I-PER				
heads	VBZ	I-VP	0				
for	IN	I-PP	0				
Baghdad	NNP	I-NP	I-LOC				
	0	0	0				
Input	Predict	ed by the organizers	Output				

The objective of the task is to recognize named entities:

- The words are the input;
- The CoNLL organizers have manually annotated the named entities; they correspond to the output;
- 3 The organizers have predicted the parts of speech and the groups to make the work easier for participants.

The Word Branch

We will now build a NER tagger that uses two inputs:

- the words and
- the parts of speech

To build a multi input network, we need the functional model and, at a certain point, merge the branches with layers.concatenate() function

The Part-of-Speech Branch

Nearly identical to the word branch:

Merging and Common Part

Code Example

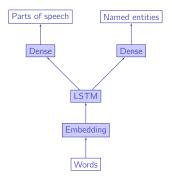
The NER tagger with two inputs: the words and parts of speech and we will compare it to a sequential model

Jupyter Notebooks: 5.2-monoinput.ipynb and

5.3-multiinput.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

The POS output

The NER Output

The Model

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

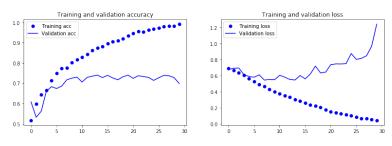
Code Example

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

Jupyter Notebooks: 5.5-multioutput.ipynb

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 provides callbacks to monitor this.

Two Callbacks

- keras.callbacks.EarlyStopping to stop training when validation scores do not improve;
- 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

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 of TensorBoard

You start it with the command:

\$ tensorboard --logdir=tb_log_folder

Jupyter Notebook:

5.6-tensorboard-salammboclassification.ipynb

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

is there not ground for suspecting that all philosophers and 10 characters, where \square marks a space:

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

Let us use this excerpt:

Generating Character Sequences with LSTMs

In addition, Chollet uses a "temperature" function to transform the probability distribution: sharpen or damp it: $\exp(\frac{\log(x)}{temp}) = x^{\frac{1}{temp}}$

```
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

From Chollet's github repository:

Jupyter Notebooks: 8.1-text-generation-with-lstm.ipynb

Machine Translation

Process of translating automatically a text from a source language into a target language

Started after the 2nd world war to translate documents from Russian to English

Early working systems from French to English in Canada

Renewed huge interest with the advent of the web

Google claims it has more than 500m users daily worldwide, with 103 languages.

Massive progress permitted by the neural networks

Corpora for Machine Translation

Initial ideas in machine translation: use bilingual dictionaries and formalize grammatical rules to transfer them from a source language to a target language.

Statistical machine translation:

- Use very large bilingual corpora;
- Align the sentences or phrases, and
- Given a sentence in the source language, find the matching sentence in the target language.

Pioneered at IBM on French and English with Bayesian statistics. Neural nets are now dominant

Italian

French

Parallel Corpora (Swiss Federal Law)

Art. 35 Milchtransport
1 Die Milch ist schonend
und hygienisch in den
Verarbeitungsbetrieb
zu transportieren. Das
Transportfahrzeug ist
stets sauber zu hal-
ten. Zusammen mit
der Milch dürfen keine
Tiere und milchfremde
Gegenstände trans-
portiert werden, welche
die Qualität der Milch
beeinträchtigen können.

lait 1 Le lait doit être transporté jusqu'à l'entreprise de transformation avec ménagement et conformément aux normes d'hygiène. Le véhicule de transport doit être toujours propre. ll ne transporter avec le lait aucun animal ou objet susceptible d'en altérer la qualité.

35 Transport du

Art. 35 Trasporto del latte

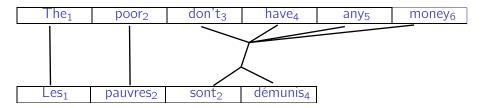
1 II latte va trasportato verso l'azienda di trasformazione in modo accurato e igienico. Il veicolo adibito al trasporto va mantenuto pulito. Con il latte non possono essere trasportati animali e oggetti estranei, che potrebbero pregiudicarne la qualità.

German

Alignment (Brown et al. 1993)

Canadian Hansard





Translations with RNNs

RNN can easily map sequences to sequences, where we have two lists: one for the source and the other for the target

у	Le	serveur	apporta	le	plat
X	The	waiter	brought	the	meal

The \mathbf{x} and \mathbf{y} vectors must have the same length.

In our case, a apporté is more frequent than apporta, but it breaks the alignment, as well as in many other examples

Translation with RNN

To solve the alignment problem, Sutskever al al. (2014) proposed (quoted from their paper, https://arxiv.org/abs/1409.3215):

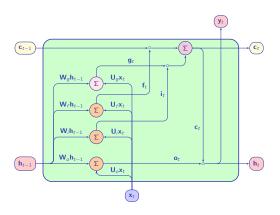
- The simplest strategy for general sequence learning is to map the input sequence to a fixed-sized vector using one RNN, and then to map the vector to the target sequence with another RNN [...]
- ② it would be difficult to train the RNNs due to the resulting long term dependencies [...]. However, the Long Short-Term Memory (LSTM) is known to learn problems with long range temporal dependencies.

Using the Hidden States

To solve the alignment problem, Sutskever al al. (2014) proposed (quoted from their paper, https://arxiv.org/abs/1409.3215):

- **1** LSTM estimate[s] the conditional probability $p(y_1, ..., y_{T'}|x_1, ..., x_T)$, where $(x_1, ..., x_T)$ is an input sequence and $y_1, ..., y_{T'}$ is its corresponding output sequence whose length T' may differ from T.
- The LSTM computes this conditional probability by:
 - First obtaining the fixed-dimensional representation v of the input sequence (x1,...,xT) given by the last hidden state of the LSTM, (encoder) and then
 - ② computing the probability of $y_1, ..., y_{T'}$ with a standard LSTM-LM formulation whose initial hidden state is set to the representation v of $x_1, ..., x_T$ (**decoder**)

The LSTM Architecture



An LSTM unit showing the data flow, where \mathbf{g}_t is the unit input, \mathbf{i}_t , the input gate, \mathbf{f}_t , the forget gate, and \mathbf{o}_t , the output gate. The activation functions have been omitted

Sequence-to-Sequence Translation

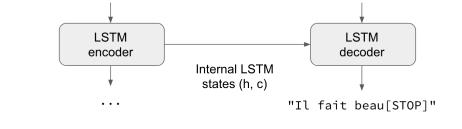
We follow and reuse: https://blog.keras.io/ a-ten-minute-introduction-to-sequence-to-sequence-learning-in html and https://keras.io/examples/nlp/lstm_seq2seq/ from Chollet.

- We start with input sequences from a language (e.g. English sentences) and corresponding target sequences from another language (e.g. French sentences).
- An encoder LSTM turns input sequences to 2 state vectors (we keep the last LSTM state and discard the outputs).
- A decoder LSTM is trained to turn the target sequences into the same sequence but offset by one timestep in the future. This training process is called "teacher forcing" in this context.
- It uses the state vectors from the encoder as initial state. Effectively, the decoder learns to generate targets[t+1...] given targets[...t], conditioned on the input sequence.

"[START]Il fait beau"

Sequence-to-Sequence Translation

"The weather is nice"



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

Inference

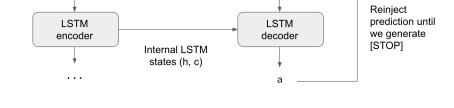
Following Chollet, in inference mode, to decode unknown input sequences, we:

- Encode the input sequence into state vectors
- Start with a target sequence of size 1 (just the start-of-sequence character)
- Feed the state vectors and 1-char target sequence to the decoder to produce predictions for the next character
- Sample the next character using these predictions (we simply use argmax).
- Append the sampled character to the target sequence
- Repeat until we generate the end-of-sequence character or we hit the character limit.

"[START]Il fait be"

Sequence-to-Sequence Translation

"The weather is nice"



From https://blog.keras.io/a-ten-minute-introduction-to-sequence-to-sequence-learning-inhtml

Improving the Architecture: Encoder-Decoder

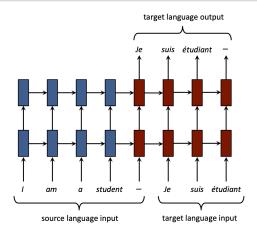


Figure 1: A simplified diagram of NMT.

From: Compression of Neural Machine Translation Models via Pruning by Abigail See, Minh-Thang Luong, and Christopher

Improving the Architecture: Adding Attention

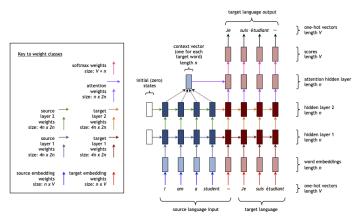


Figure 2: NMT architecture. This example has two layers, but our system has four. The different weight classes are indicated by arrows of different color (the black arrows in the top right represent simply choosing the highest-scoring word, and thus require no parameters). Best viewed in color.

From: Compression of Neural Machine Translation Models via Pruning by Abigail See, Minh-Thang Luong, and Christopher

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Further Readings

- For the latest developments, see: http://www.statmt.org/wmt20/
- For a description of systems with attention, see https: //www.tensorflow.org/tutorials/text/nmt_with_attention and https://www.tensorflow.org/tutorials/text/transformer
- For an example attention program in Python, see, https://machinelearningmastery.com/
- encoder-decoder-attention-sequence-to-sequence-prediction
- For another tutorial using pytorch: https://pytorch.org/tutorials/intermediate/seq2seq_ translation_tutorial.html