

COMP3220 — Document Processing and the Semantic Web

Week 06 L1: Advanced Topics in Deep Learning

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COMP3220 2021H1

Programme

- 1 Text Generation
- 2 Encoder-Decoder Architecture
- 3 Pre-training and Fine-tuning

Reading

- Deep Learning book, section 8.1.

Additional Reading

- Jurafsky & Martin, Chapter 9.
- The Illustrated BERT, ELMo, and co.:
<http://jalammr.github.io/illustrated-bert/>

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Generating Text Sequences

- One of the advances of deep learning versus shallower approaches to machine learning is its ability to process complex contexts.
- This has allowed significant advances in image and text processing.
- We have seen how to process text sequences for text classification.

Text generation as a particular case of text classification

- Given a piece of text ...
- Predict the next character.

Text Generation as Character Prediction

- Our training data is a set of samples of the form:
 - Input** Text fragment.
 - Label** Next character to predict.
- We do not need to manually annotate the training data: the data are self-annotated.
- This means that we can easily gather training data for text generation.
- This is the idea for training language models (next slide).

Language Models

- Given a collection of text, we can train a **language model** that can be used to generate text in the same style.

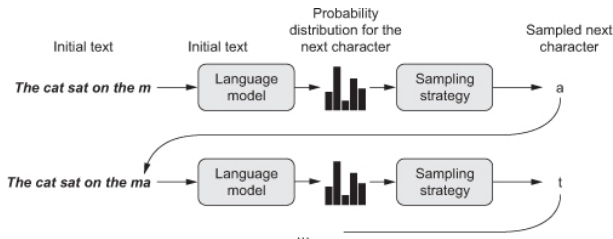


Figure 8.1 of Chollet (2018).

Implementing Character-level LSTM Text Generation

- The architecture of the model is of the kinds we have seen for text classification.
 - The input is a sequence of characters.
 - The “class” to predict is the next character to generate.
- If we add an embedding layer after the input, This layer will learn **character embeddings**.

```
model = tf.keras.models.Sequential()  
model.add(layers.Embedding(len(chars), 20, input_len=maxlen))  
model.add(layers.LSTM(128))  
model.add(layers.Dense(len(chars), activation='softmax'))
```

Generating Text



- Remember that the output of a prediction is a probability distribution.
- To generate the next character, we can **sample from the probability distribution**.
- We can determine how deterministic the sampling is:
 - We can always return the character with highest probability ...
 - Or we can select a character randomly ...
 - Or we can do something in between, according to a “temperature” parameter.

```
import numpy as np
def reweight_distribution(original_distribution, temperature=0.5):
    distribution = np.log(original_distribution) / temperature
    distribution = np.exp(distribution)
    return distribution / np.sum(distribution)
```


Figure: Different Reweightings

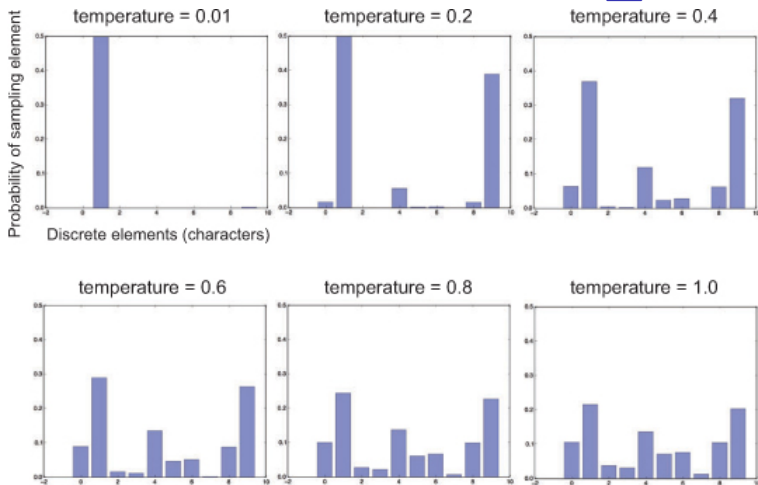


Figure 8.2 of Chollet (2018)

Example



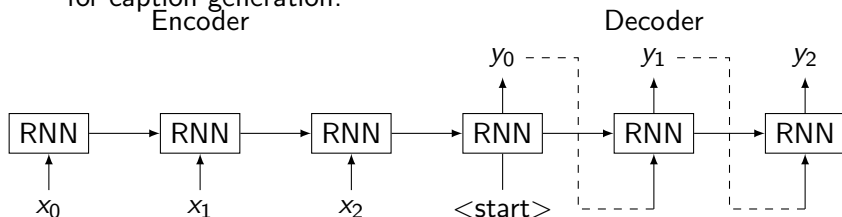
See notebook ...

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The Encoder-Decoder Architecture

- Composed of an **encoder** and a **decoder**.
 - The encoder can be an RNN chain that takes the input.
 - The decoder can be an RNN that takes the output of the previous RNN as input.
- Revolutionised machine translation and many other text processing applications.
- The encoder stage can be something non-textual, e.g. images for caption generation.

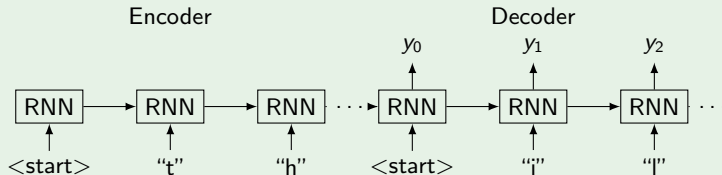


Training the Encoder-Decoder Architecture

A common approach to train the encoder-decoder architecture is to apply **teacher forcing**:

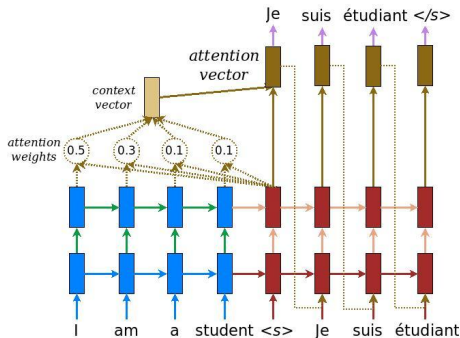
- Use the target sequence to guide the training of the decoder.
- For example, in an English to French machine translation system, we feed the target French translation to the decoder.

“The weather is fine” → “Il fait bon”



Attention: An Improvement to the Encoder-Decoder Architecture

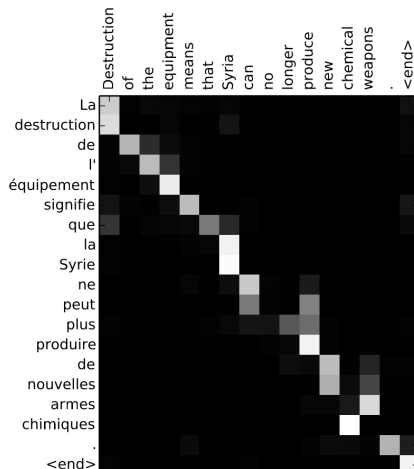
Attention is an enhancement in the seq2seq architecture that allows to focus on parts of the input during the generation stage by the decoder.



https://github.com/tensorflow/tensorflow/blob/r1.13/tensorflow/contrib/eager/python/examples/nmt_with_attention/nmt_with_attention.ipynb

Attention for MT

Very useful to start understanding the decision processes of the model.



Attention in Caption Generation



A woman is throwing a frisbee in a park.

Xu et al. (2015) [arXiv:1502.03044](https://arxiv.org/abs/1502.03044)

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Problems with Supervised Learning

Annotated data

- Supervised learning requires (a lot of) **annotated** data.
- Annotated data can be costly.
- Human annotated data can contain annotation errors.

Training size

- Supervised learning requires **a lot of** (annotated) data.
- Large companies can afford the resources for processing large volumes of data, others can't.
- Some domains do not have much text anyway.

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Artificial intelligence / Machine learning

Training a single AI model can emit as much carbon as five cars in their lifetimes

Deep learning has a terrible carbon footprint.

by **Karen Hao**

June 6, 2019

<https://www.technologyreview.com/2019/06/06/239031/training-a-single-ai-model-can-emit-as-much-carbon-as-five-cars-in-their-lifetimes/>

Idea: Pre-Train and Fine-Tune

Pre-training

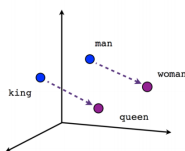
- Develop a system that can be trained with large volumes of data.
- Make the system as general as possible, so that it can be used for multiple tasks.

Fine-tuning

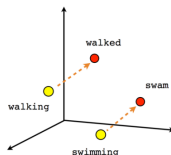
- Design a Deep Learning model that contains:
 - A layer pre-trained for a general task.
 - Additional layers that adapt the general task to our specific task.
- Fine-tune the system using the (smaller) training data of our specific task.

Example: Word Embeddings

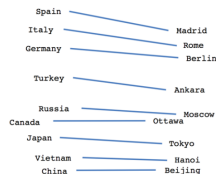
- As we have seen in a previous lecture, word embeddings can be learnt using large, unlabelled data.
- These pre-trained word embeddings can be used to initialise an embeddings layer in our Deep Learning model.
- We have the choice to update these word embeddings, or not.



Male-Female



Verb tense



Country-Capital

Huggingface's transformers library



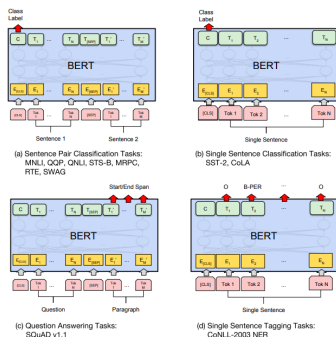
Transformers

<https://github.com/huggingface/transformers>

- Huggingface's **transformers** library contains a large repository of pre-trained models.
- These models are contributions from many researchers and developers.
- These models are being used to obtain state-of-the-art results.

Example: Using BERT in Keras

- BERT is one of the most popular architectures for pre-training and fine-tuning.
- Look at the lecture notebook for an example of use in keras.
- BERT is easy to use, but fine-tuning can take a long time.



Take-home Messages

- 1 Text generation as a task of character (or word) prediction.
- 2 Describe the encoder-decoder architecture. What is this architecture good for?
- 3 What is teacher forced training and what is it good for?
- 4 Transfer learning and fine-tuning.

What's Next

Weeks 7-12

- Semantic Web (Rolf Schwitter).
- Assignment 2 submission deadline on Friday 23 April 2021.