# Notes on Natural Language Processing with Transformers by Lewis Tunstall and Leandro von Wierra

compiled by D. Gueorguiev 3/30/24

## Introductory Notes

### The Encoder-Decoder Framework

Prior to transformers , recurrent architectures such as LSTM were popular in NLP. These architectures contain a feedback loop in the network connections that allow information to propagate from one step to another, making them good for modeling sequential data like text. An RNN receives an input (word or character), feeds it through the network and outputs a vector called *hidden state*. The model feeds some information back to its output through a feedback loop, which it can use on the next step. Unrolling the loop produces the “unrolled” network shown below: the RNN passes information about its state at each step to the next operation in the sequence – in a sense this simulates a memory attached to the network which collects condensed representation of the previous states which it uses in its sequential predictions.

State

RNN cell

Input

State

RNN cell

Input

State

RNN cell

Input

State

RNN cell

Input

State

RNN cell

Input

Figure: Unrolling an RNN in time

RNN cell

RNN cell

RNN cell

RNN cell

RNN cell

RNN cell

RNN cell

RNN cell

State

Transformers

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Figure: An encoder-decoder architecture with a pair of RNNs

For details on this RNN-based architectures refer to [2] in the Reference section.

Basics of Transformers

The Transformer architecture excels at

## Appendix

### Unreasonable Effectiveness of Recurrent Neural Networks

#### RNNs

What makes Recurrent Networks special?

Limitation of Feed Forward Networks and also Convolutional Networks:

that their topology is too constrained: They accept a fixed size vector as input (for example an image) and produce a fixed-sized vector as an output (for example probabilities of different classes). This kind of networks also perform their mapping using a fixed amount of computational steps because there are fixed number of layers in their topology.

RNNs do not have some of these constraints. The topology of the RNNs allow to operate over a *sequence of vectors* rather than just individual vectors.

A diagram of a number of rectangular objects

Description automatically generated with medium confidence ( 1 ) ( 2 ) ( 3 ) ( 4 ) ( 5 )

Figure: Each rectangle is a vector. Arrows represent functions (e.g. matrix multiply). Input vectors are shown in **red**. Vectors which hold the network state are shown in **green**. Output vectors are in **blue**.

( 1 ) denotes traditional processing in vanilla feed forward network which uses fixed-size input and has fixed-size output. Example: *image classification* with CNN. ( 2 ) sequence output topology – input has fixed size and output is of variable size i.e. *sequence output*. Example: *image captioning* which takes an image (fixed-size input) and outputs a sentence of words. ( 3 ) sequence input and fixed size output. Example: *sentiment analysis* where given sentence is classified as expressing positive or negative sentiment. ( 4 ) sequence input and sequence output. Example: *machine translation* where an RNN reads a sentence in English and outputs a sentence in French.

( 5 ) synced sequence input and output. Example: video classification where the goal is to label each video frame.

*Note*: in each of the relevant topologies there are no pre-specified constraints on the sequence lengths because the recurrent transformation can be applied as many times as we want.

Sequential processing in absence of sequences

Even if the inputs/outputs are fixed vectors it is still possible to use RNNs to process the inputs in sequential manner. For example, in [3] sequencing of the input is achieved through the implementation of a form of attention which the authors call *glimpse*. The network uses information from the glimpse to update its internal representation of the input, and outputs the next glimpse location and possibly the next object in the sequence. The process continues until the model decides that there are no more objects to process. The proposed system can be trained end-to-end by approximately maximizing a variational lower bound on the label sequence log-likelihood. This training procedure can be used to train the model to both localize and recognize multiple objects purely from label sequences. Let us discuss the proposed in [3] *deep recurrent visual attention model*.

Deep recurrent visual attention model

The deep recurrent visual attention model can be applied to classifying a single object and also can be extended to multiple objects. Here are the details – processing an image with an attention-based model is a sequential process with steps, where each step consists of a saccade followed by a glimpse. At each step , the model receives a location , along with a glimpse observation taken at location . The model uses the observation to update its internal state and outputs the location to process at the next time-step. Usually the number of pixels in the glimpse is much smaller than the number of pixels in the original image , making the computational cost of processing a single glimpse independent of the size of the image.

A graphical representation of this model is shown on the Figure below. The model can be broken down into a number of sub-components, each mapping some input into a vector output.

A diagram of a block diagram

Description automatically generated

Figure: a graphical representation of deep RNN with visual attention

**Glimpse network**: The glimpse network is a non-linear function that receives the current input image patch, or glimpse, or a glimpse, and its location tuple , whee , as input and outputs a vector . The glimpse network extracts a set of useful features from location of the raw visual input. We will use to denote the output vector from function that takes an image patch and is parametrized by weights . A typical construction of is with three convolutional hidden layers without any pooling layers followed by fully connected layer.

RNN computation

## References

## [1] [Natural Language Processing with Transformers, Lewis Tunstall, Leandro von Werra, Thomas Wolf, 2022](https://github.com/dimitarpg13/transformers_intro/blob/main/articles_and_books/natural-language-processing-with-transformers-revised-edition-book.pdf)

[2] [The Unreasonable Effectiveness of Recurrent Neural Networks, Andrej Karpathy blog, May 21, 2015](https://karpathy.github.io/2015/05/21/rnn-effectiveness/)

[3] [Multiple Object Recognition with Visual Attention, Jimmy Ba, Volodymyr Mnih, Koray Kavukcuoglu, 2015](https://github.com/dimitarpg13/deep_learning_and_neural_networks/blob/main/literature/articles/Multiple_Object_Recognition_with_Visual_Attention_Ba_Mnih_2015.pdf)

[4] [Long Short-Term Memory, Sepp Hochreiter et al., 1997](https://github.com/dimitarpg13/transformers_intro/blob/main/articles_and_books/LongShortTermMemory.pdf)

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[8] [Turing Computability with Neural Nets, Hava T. Siegelmann, Eduardo Sontag, 1991](https://github.com/dimitarpg13/deep_learning_and_neural_networks/blob/main/literature/articles/computability/TuringComputabilityWithNeuralNets_Siegelman1991.pdf)

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