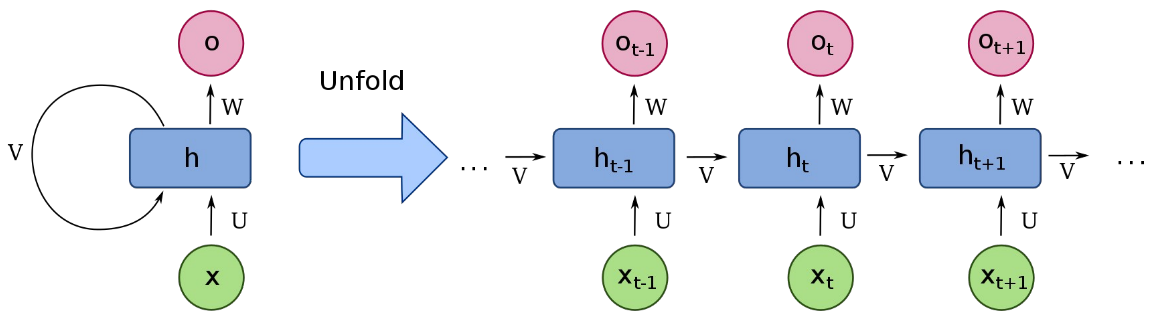
#I would like to have a grade

Report on what I wanted to do as a project for the course „Python für Fortgeschrittene – Wissenschaftliche Anwendungen“ an what I learned on the way by failing to produce a working self made solution.

My first Idea was to devle further into the topic of neural networks and machine learning after introducing the first basic concepts in the lecture.
The self set aim was the to consider data in an ordered sequence like text musik statistics data in time to make predictions for a given startinput about the further development of that sequence based on the trainingsdata. So the idea of a NLP (Natural Language Processing) related work was set. As text as well as stocks seemed a common idea and on first sigth not that funny, I wanted to try a simple music generation.

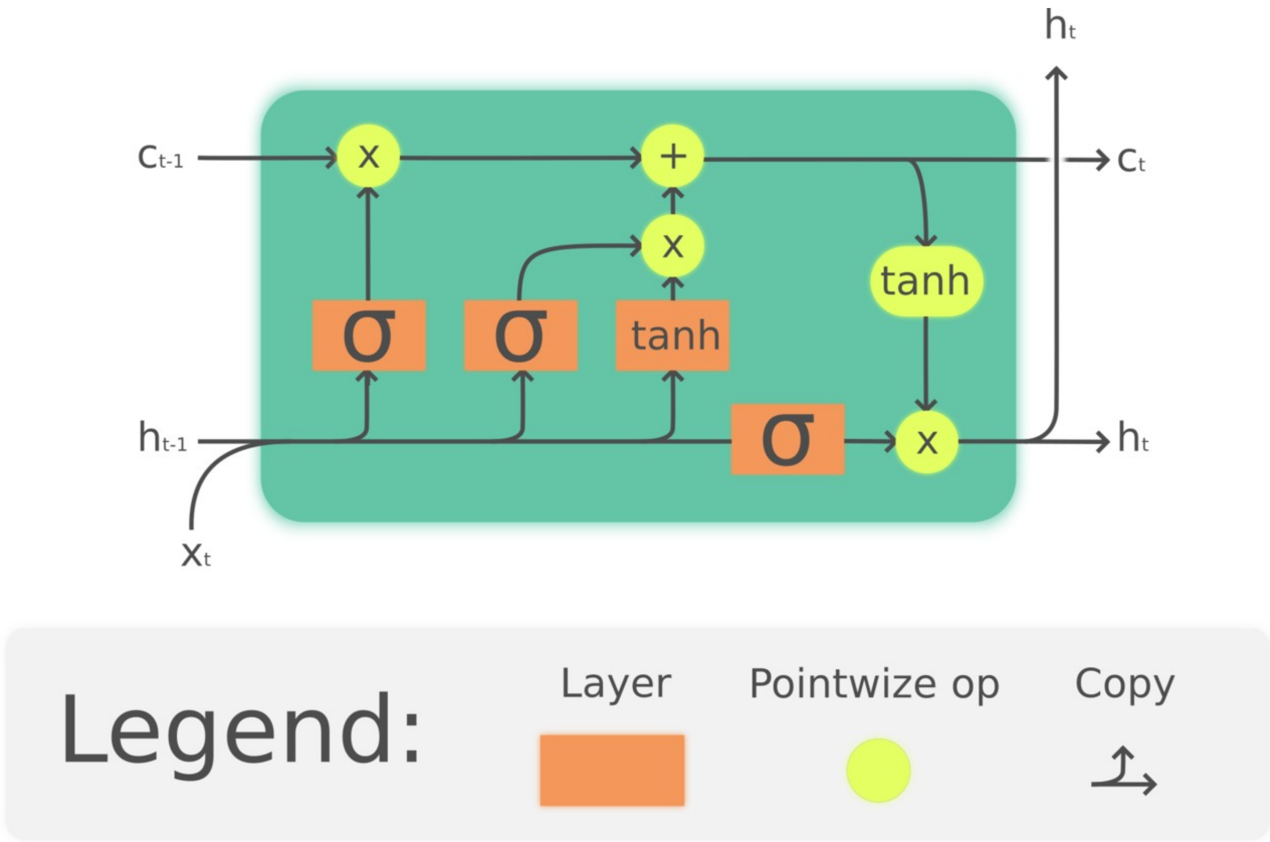
RNN:
Therefore I first started to understand what RNN's (recurrent neural networks) are. It is possible the simpliest way to keep track on previous seen data in an ongoing sequence. The idea is that every cell in addition to a standard cell has a hidden state containing information on the past inputs. The generated output is then computed not only by the given input but also with the help of the hiddenstate to take the previous data into account. While the output is processed also a new hidden state has to be computed to keep track of the past input.



The picture shows a cell of a RNN and its unfolding where x is the input o the output and V the update of the hiddenstate after each step.

To train such a network normal backpropagation wouldnt work anymore but one has to do a backpropagation through time since also all the hiddenstates have to be updated. This results in a lot of matrixmultiplications wich lead to heavy problems with vanishing gradients.
This is one of the major drawback of RNN's and cristallises to the effect that it has a rather short memory of previous structur and dependencies. (Exploding gradients are a problem to but can relativly easy be solved by normalisation between the computations also called gradient clipping)
There are a few concepts for RNN's to attac these problem keeping the style of the RNN structure but I didn't read further into it since the next step in the evolution of sequential neural networks tackel exactly this problem.

LSTM
So next on I studie LSTM neural networks (long short time memory), rely on a lot more computation by intruducing methods to decied on the relevance of historical information delets irrelevant information and also decides about importance of input information.



C: cell state; h: hiddenstate; X: input
Going from left to right first unneccesary data of the previous state is forgoten (forget gate) then relevant information of the new input is stored, after that the status is updated and alst outputted.

The big advantage in comparism to RNN’s is that we have an uninterupted gradientflow along the cell states wich means we migitate the Proble of vanishing gradient while training the model using gradient descent. (notice that all the operation in updating the cellstate C are pointwise operations)

A very similar approch as LSTM are GRU (Gated Recurrent Units) but I have no deeper konwledge about them

LSTM’s were used by companys like google or facebook for translation tasks a few years ago. (most likely the where replaced by better performing networks)

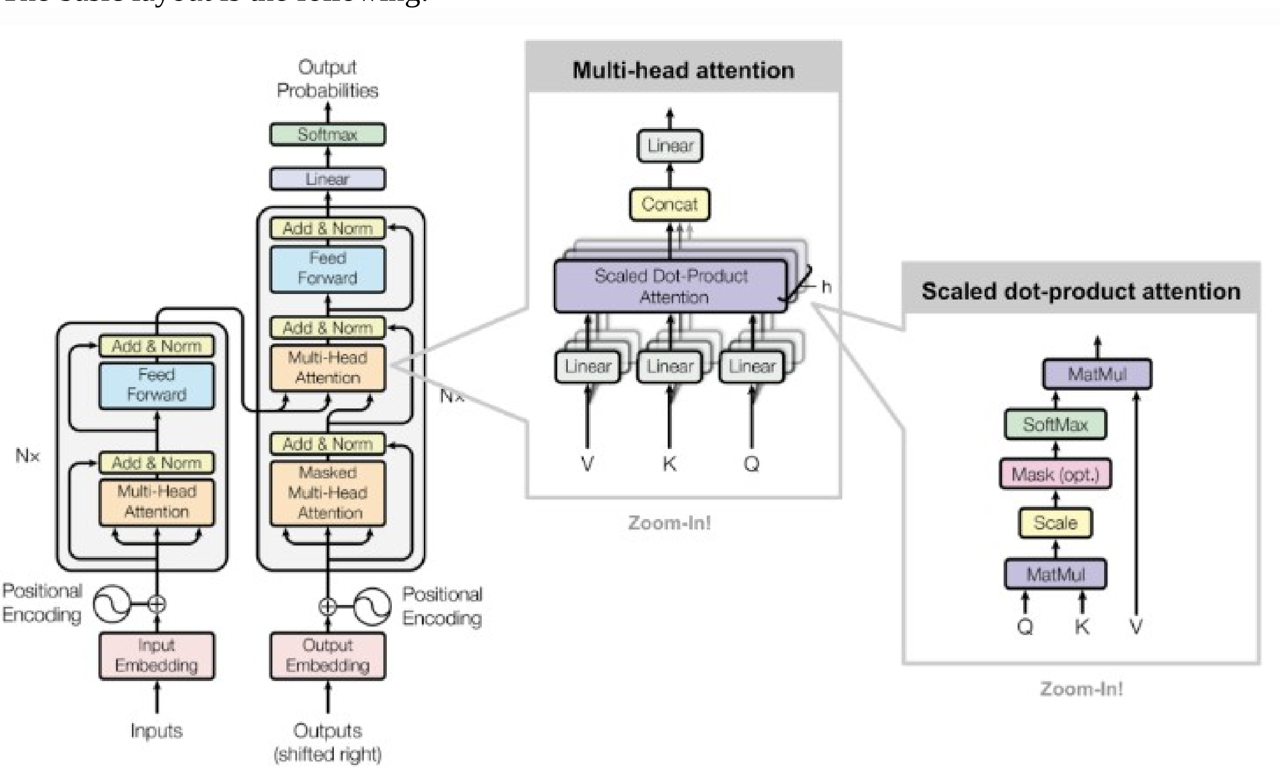
Transformer:
One probably the biggest problem all the mentioned networks share is that they have to be computed step by step due to their serial structure. This means that they cant make use of parallelisation as offerd by gpu’s and multicore cpu’s (wich nowadays is the most common way to reduce computation time).

This Problem was addressed in a paper of 2017 namely “Attention is all you need” (https://arxiv.org/abs/1706.03762), where a new model of neuralnetwork is introduced, called the transformer.

This model uses attention maps to determine the relevance of information via weights. Whats new to the already known attention mechanism, wich computes attention between input sequence and

outbut sequence, is that they proposed self attention wich is used to determin the relevance of information between different position of the input sequence.
As the title of the paper suggests, transformer utilices selfattention without using any RNN’ related structure.
A lot of time (~12h) of the originall 24h went into understandig this paper by reading it, wwatching explanation videos and by experimenting with the tensorflow tutorial implementation example of trasnformer. (https://www.tensorflow.org/tutorials/text/transformer) (this is quite nice)

The basic layout is the following:



Source: Attention is all you need

Scaled dot-product attention: An attention mechanism where query and key values are multiplied then scaled to minimize problems with small gradients (due to large numbers after huge matrices multiplied). The mask is used to hidde information aside witch lies in the future (sequnece positions still to come). After that a activation function is applied and after that a dot product with the Value matix.

Multihead attention: Values, keys, and querys are split into linear projection then attention is apllied and afterwards concatenated instead of apllying the attention to the whole matrices, at he end everything is finaly projected to obtain the output. Splitting into subspaces has the advantage that every attention head “see’s” anothertype of information and therefore can reckognice different patterns.

Positional encoding: This is important since we need the information where in the sequence we are, without this the model would just see a bag of words since it has no information about position. This is done by using sin and cos on the even/odd positions and with differnent frequencies to encode the relative position.

Encoder (left):

Takes a input runs the positional encoding and applies selfattention to the input add the result to the input (residuall concetion) and applies a layer normalisation. (Think of batch normalisation/ There is a whole paper on laer noramlization(used where batch normalisation wont work))
Afterwards a classical feedforward network is applied and again added and normalized.

Decoder (right): From bottom to top First the output shifted rigth to get the nex step in the sequence is positinaly encoded. Then as in the encoder selfattention is applied and the result added and normalized. This result is feeded as the query into a multihead (not self attention but “classic” attention) where Values and keys are obtatined from the encoder. Again this is added and normalized and finaly processd throug a feed forward network, added and normalized.

To finish after encoder and decoder the result is projected and runs throug an activation function, in the paper a softmax was chossen, to obtain a probability ditribution of the next token in the sequnece.

The tensorflow tutorial for transformer straigth forward implements this picture, and it works quite nice. As one migth assume even for small text klength it already takes quite a lot of time to train such a model, but the positive effect is that one has to train the model only once and can use it afterwards. Also one can notice that one can checkpoint the training so if no changes were made to the code till training the network the model cann still be used or loaded.

After spending so much time understanding the model, I decied to get started with the idea to use the transformer model as proposed in “attention is all you need” and try to build a simple music generator out of it. There would have been further paper on this topic and also a bunch of eloborated examples with this more elaborated models but I reckogniced that I dont have that much spare time and I wanted to come up with a solution by my own so I dindt wanted to read the projects code.

About music generation
Music is like language a sequnece of notes but unlike words the are not that easy to tokenize since a single note has more information than a word. A word can be easily tokenized via a dict but a single note has the information about pitch, start time, endtime, velocity if we consider music in the form of a midi file (wich we will for simplicity other formats can be converted to midi using some kind of fourier transformation algorythms)
So there are several ways to do this for suggestions see mangenta or (https://towardsdatascience.com/practical-tips-for-training-a-music-model-755c62560ec2)
This has to be done for every instrument witch adds complexity and computaional time therefore I considered only pieces with piano.
Note that we also didnt talk about chords witch can/should be handeld separatly for beautifull results.

Then one has to convert these tokenized songs into bunched up training data.

It should be noteted that every song should be in the trainings data several times with different pitch offset since for us to melodies in differnte octaves sound the same melody wise but are not the same for a neural network.

Creating a usefull dataset to train the the transfomernetwork to predict next tokken/note in a melody for a given start sequenc is my main problem wich a wasn’t able to fix yet also I’m already 35+

hours in due to my overintrest of more knowledge of neural networks and overconfidence to get the project done straitgh from theoretical knowledge.

The aim is to get the project done somewhere in the future but I cant keep infesting all spare time into this. Nevertheless it was an intensive time working on this the last two weeks and in my feeling I now have a better understanding concerning recent neural networks.

Since there is quite a bit of time between the test runs I digged a little bit deeper into state of the art NLP neural networks and found that a lot of recent papers where published to improve the transformer model significantly and to utilize and alter it for specific tasks.
Notable: Transformer XL ; GPT2 by openAi (state of the arte translation network)

In the git repository there is also a link of interessting articels I read and found usefull.