Intro to deep learning

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Lecture 10: Recurrent Neural Networks

Motivation

Today you will see how a bunch of matrix multiplication can generate text and translate from English to German

Topics

- Recap: Tokenization and embeddings
- `dataclasses` to store Parameters
- Language modelling with simple Recurent Neural Networks
- Machine translation with the encoder-decoder RNN
- Problems of RNNs

Recap: Tokenization and embeddings

- Tokenization: Convert text to integers
    - Character level
    - (Sub-)word level
- Input embeddings: Convert tokens to one-hot vectors
- Example: `` `"hello"` ``
    - Vocabulary: ["e", "h", "l", "o"]
    - Vocabulary size: 4
    - Tokens: [1, 0, 2, 2, 3]
    - Embedding of "h": array([0, 1, 0, 0])

Task 1

Storing parameters

- In our first network
  - List of three weight matrices
  - List of three bias vectors
- Today:
  - 5 different matrices
- Need to bundle them to reduce complexity

Option 1: Dicts

```python
p = {
  "w": np.array(...),
  "b": np.array(...),
}

relu(p["w"] @ x + p["b"])
```

- Pros:
  - Name based access
  - We already know dicts
  - Very lightweight
- Cons
  - `` `p["w"]` `` is not pretty
  - No autocomplete
  - Easy to have typos

Option 2: Class

```python
class Params:
    def __init__(self, w, b):
        self.w = w
        self.b = b

p = Params(w, b)
p
```

```
<__main__.Params at 0x7f66f8120350>
```

- Pros:
  - Autocomplete and typo corrections
  - `p.w` access works
- Cons
  - Redundant typing
  - No nice string representation

Best of both worlds: dataclass

```python
from dataclasses import dataclass

@dataclass
class Params:
    w: np.ndarray
    b: np.ndarray

w = np.ones(3)
b = np.arange(3)
p = Params(w, b)
p
```

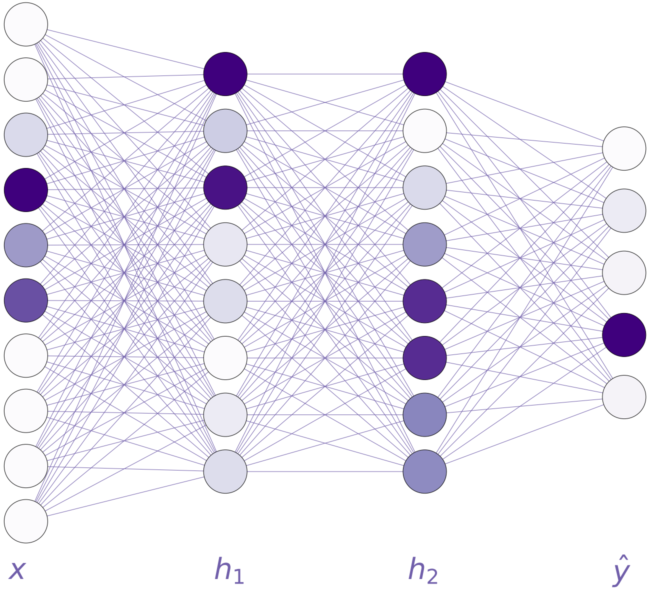
```
Params(w=array([1., 1., 1.]), b=array([0, 1, 2]))
```

- Less typing
- Type hints are self documenting
- Better string representation
- Built into Python
- More information: Video by Raymond Hettinger

Language modelling

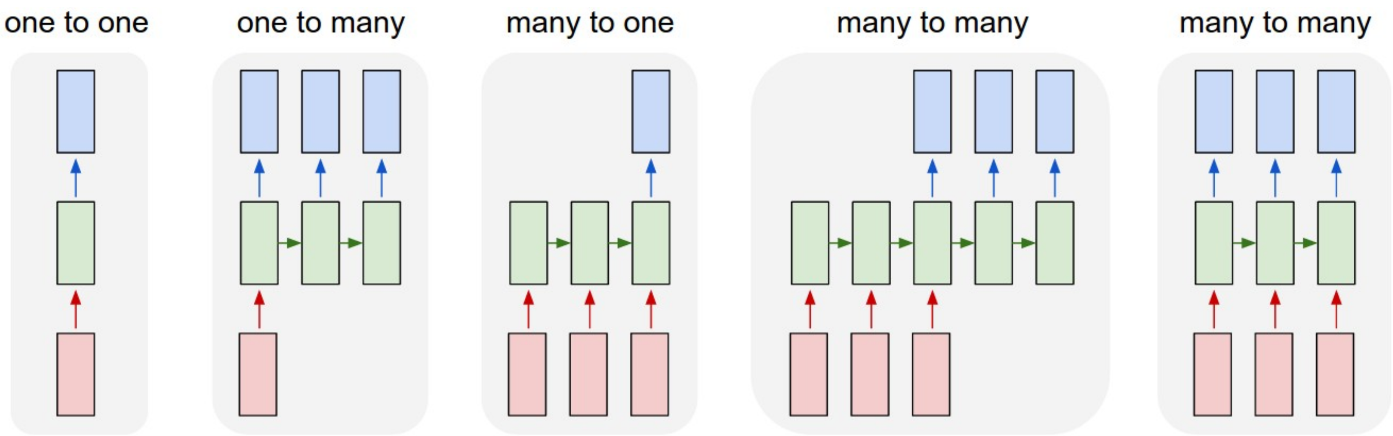
- Language model is a precisely defined type of model
- Task: Given a sequence of text, predict the next word
- More precisely: predict probability distribution over next word
- Input sequences of different lengths
- Most famous example: GPT

Why our simple model can't do this



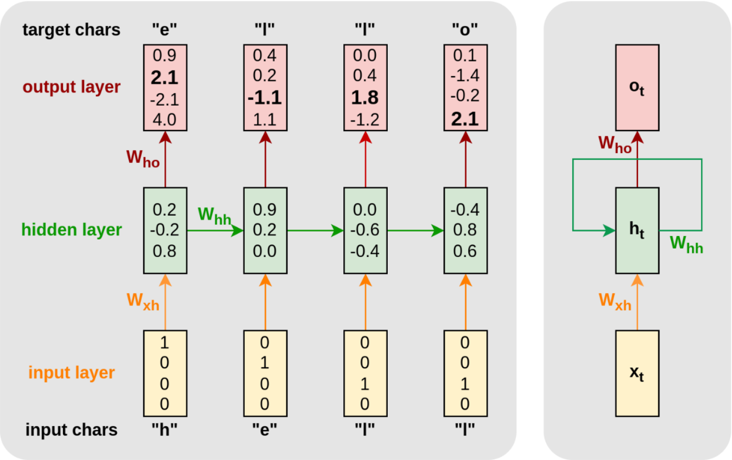
- Fixed size of model inputs
- No memory between inputs

Model interfaces



1. Image classification
2. Image captioning
3. Text classification
4. Machine translation
5. Language modelling

The simple RNN on one slide



Source: Tobias Stenzel's Blog

- 3 Different weight matrices
- Weights stay the same between time steps
- Left: unrolled representation
- Right: recurrent representation
- $h_t = tanh(W_{hh} \cdot h_{t-1} + W_{xh} \cdot x_t)$
- $y_t = W_{hy} \cdot h_t$

Task 2

A few more details

- The model step:
  - $h_t = tanh(W_{hh} \cdot h_{t-1} + W_{xh} \cdot x_t)$
  - $y_t = W_{hy} \cdot h_t$
- This step is called once for each input embedding
- The initial hidden state is a vector of zeros

Task 3

The loss function

- Goal: Model should be good at predicting likely next words
- Same likelihood/crosse-entropy approach as before
- A sequence of 5 tokens contains four training examples

```
"h", "e", "l", "l"
"e", "l", "l", "o"
```

Goal for the training in our example

- We just want the model to memorize the word hello
- See it as proof of concept
  - Information can be encoded in parameter matrices
  - RNN is a suitable model structure
- No holdout sample
- No worry of overfitting

Large models

- Language models are trained on "a good chunk of the internet"
- Typically, just one epoch to avoid overfitting

Task 4

Writing the sequence-to-sequence function

- The model is not yet text-to-text
- Need a function that looks as follows:

```
def s2s_model(text, p, vocabulary):
    # tokenize the text
    # call the model
    # translate the output embeddings into text
```

Task 5

Language models for question answering

- Reminder: Language model = model that predicts a likely next word
- Can be used very creatively
- For example, what is the likely continuation of this sequence?

```
10 + 5 = 15
3 + 41 = 44
11 + 7 =
```

- Similar approaches convert language models to chat bots

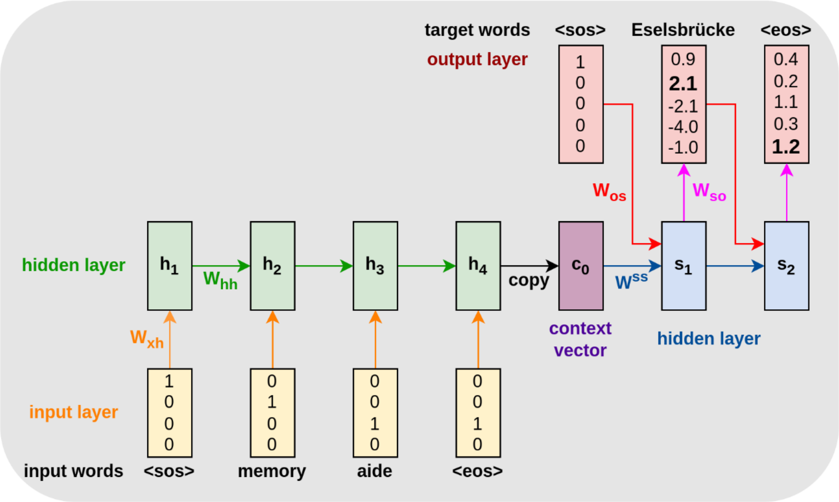
How to go deeper

- Our RNN:
  - took input embeddings as input
  - returned output embeddings
- We could stack another network on top that
  - takes the output embeddings of the first network
  - produces other output embeddings
- Each network is called an RNN cell
- Parameters are not shared across RNN cells!
- This is just what happens in deep recurrent neural networks

Machine translation

- Language models can also be used for translation
- However, they are not the most efficient at that
  - input and target sentence might have different lengths
  - order of words might be different
- Encoder-Decoder Architecture solves exactly that

The encoder-decoder architecture



Source: Tobias Stenzel's Blog

- Encode step is as before but not producing `y`s
- Final hidden state becomes initial decoder state
- Decode step is similar to before:
  - Takes embedding of previous y as input
  - Maintains an internal state
  - Produces new `y`s from previous `y` and internal state

Properties

- Output sequence can now have different length than input sequence
- First produced token can take the entire input into account
- Parameters are not shared between encoder and decoder
  - In total 5 parameter matrices
- There is an input and output vocabulary
- We need a start and end token

New example

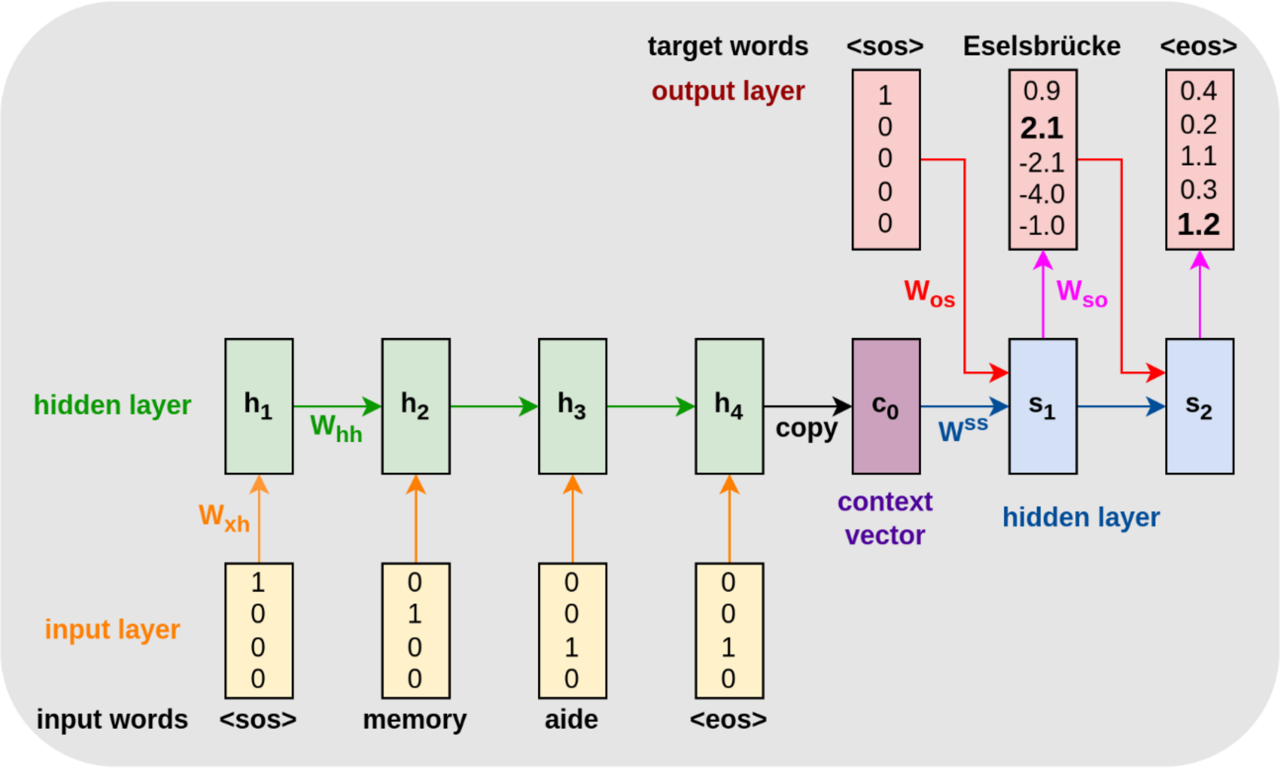
- Translate "hello world" into "hallo welt"
- Use word level embedding
- With `<SOS>` and `<EOS>` vocabulary size is 4
- Implement tiniest possible network that can memorize the correct translation!

Encoder and decoder steps

- Encoder step
  - $h_t = tanh(W_{hh} \cdot h_{t-1} + W_{xh} \cdot x_t)$
  - Same as before but no equation for `y`
- Copy step:
  - $s_0 = h_T$
- Decoder step
  - $s_t = tanh(W_{ss} \cdot s_{t-1} + W_{ys} \cdot y_{t-1})$
  - $y_t = W_{sy} \cdot s_t$
  - y_{t-1} plays role of x_t; Rest as before

Task 6

Unrolled representation



Source: Tobias Stenzel's Blog

Task 7

Differences for text-to-text model

- Previously: One vocabulary
- Now: Input and output vocabulary
- Be careful to use the right vocabulary in each step

Task 8

Summary

- Feed-forward neural networks need fixed input and output size and have no memory
- RNNs are the simplest networks that can have variable size inputs and/or outputs
- Our models were tiny and could only memorize one task!
- For more useful networks you have to make them larger and deeper
- Next week we will see more complex architectures for the same cases

Problem of RNNs

- RNNs have two problems:
  1. They cannot model relationships between words that are far apart
  2. They are hard to train
- Both come inherently from the recurrent structure where the "memory" vector h gets multiplied over and over again by the same matrix W_{hh}
- There are ways to mitigate that (LSTM-RNNs)
- They were state of the art until 2017 but are now replaced by transformers
- We will skip LSTMs and move directly to transformers