The Unreasonable Effectiveness of RNN: an introduction to recurrent neural networks

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THE INTRODUCTION

The Motivation for RNN

- One can distinguish two major families of neural networks:
  - A-cyclic graphs define feed-forward networks (FFN)
  - Cyclic (self-referencing) graphs define recurrent networks (RNN)
- Their use depends on the problem at hand
- Feed-forward nets can be thought of as optimizing over functions
- Recurrent nets are more like optimizers over programs: precesses in time
- Early RNN suffered form the 'Vanishing Gradient Problem', limiting their use
- VGP made it hard for RNN to represent large scale correlations in data
- Long-Short Term Memory (LSTM) introduced in 1997 resolved this issue and unlocked the potential of RNN
- RNN mimic brain structures much more closely that FFN and are fascinating dynamical systems...

Recent Successes of RNN

- RNN with LSTM are praised for outstanding performance in many tasks:
  - Natural language processing: on-line translation
  - Image captioning
  - Text generation
  - Picture and music generation
  - Pattern recognition with long range (temporal) correlations
- It is therefore natural to try understanding their properties
- First however we shall review some basic concepts from FFN networks

NEURAL NETWORKS BASICS

The Basic Unit: Artificial Neuron Node

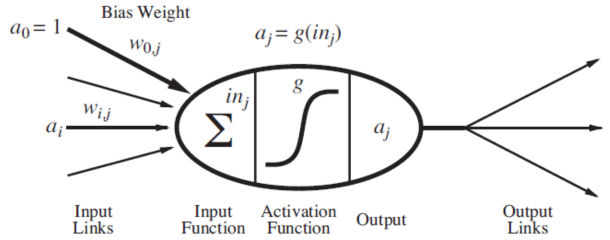


Figure 18.19 A simple mathematical model for a neuron. The unit's output activation is $a_j = g(\sum_{i=0}^{n} w_{i,j} a_i)$, where a_i is the output activation of unit i and $w_{i,j}$ is the weight on the link from unit i to this unit.

The Simplest FF Nets: The Perceptron and Hidden Layer

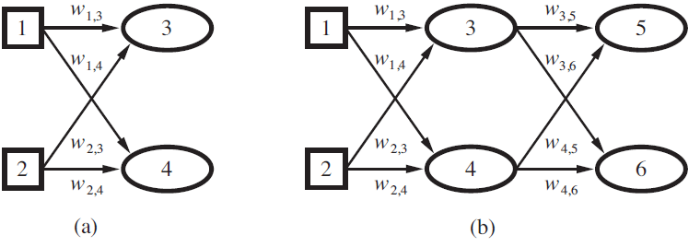


Figure 18.20 (a) A perceptron network with two inputs and two output units. (b) A neural network with two inputs, one hidden layer of two units, and one output unit. Not shown are the dummy inputs and their associated weights.

FFN Output as Nested Functions

- FFN network is a function h of its input data x: $h_W(x)$
- Internal state of FFN is defined by the link weights W
- Activation can be *tanh*() or some other step-like function
- In essence FFN is just a collection of highly nested functions, e.g.:

$$
\begin{aligned}
a_5 &= g(w_{0,5,+} w_{3,5}\, a_3 + w_{4,5}\, a_4) \\
&= g(w_{0,5,+} w_{3,5}\, g(w_{0,3} + w_{1,3}\, a_1 + w_{2,3}\, a_2) + w_{4,5}\, g(w_0 4 + w_{1,4}\, a_1 + w_{2,4}\, a_2)) \\
&= g(w_{0,5,+} w_{3,5}\, g(w_{0,3} + w_{1,3}\, x_1 + w_{2,3}\, x_2) + w_{4,5}\, g(w_0 4 + w_{1,4}\, x_1 + w_{2,4}\, x_2)).
\end{aligned}
$$

- Training amounts to adjusting W so to minimize squared errors from the expected output y:

$$Err_2 = \frac{1}{2}(h_W(x) - y)2$$

FFN Training: Backpropagation

- We provide training data x with expected FFN outcomes y
- We would like to reduce the errors $(y - h_W(x))$
- The sign of this expression dictates how we should alter weights W
- The error at output node j is used to define a modifier $\Delta[j]$:

$$\Delta[j] = g'(in_j)(y_j - a_j)$$

- It is subsequently backpropagated through the network with fractional weights:

$$\Delta[i] = g'(in_i) \sum_j w_{i,j} \Delta[j]$$

  and finally used in the main W substitution rule (for all layers):

$$w_{i,j} \leftarrow w_{i,j} + \alpha\, a_i\, \Delta[j]$$

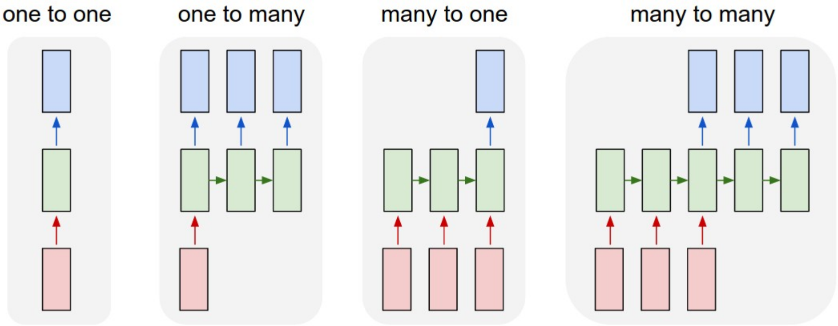
- Hyperparameter α defines the learning rate

function BACK-PROP-LEARNING(*examples*, *network*) **returns** a neural network
  inputs: *examples*, a set of examples, each with input vector $\mathbf{x}$ and output vector $\mathbf{y}$
    network, a multilayer network with L layers, weights $w_{i,j}$, activation function g
  local variables: Δ, a vector of errors, indexed by network node

  repeat
    for each weight $w_{i,j}$ in *network* **do**
      $w_{i,j} \leftarrow$ a small random number
    for each example $(\mathbf{x}, \mathbf{y})$ **in** *examples* **do**
      / Propagate the inputs forward to compute the outputs */*
      for each node i in the input layer **do**
        $a_i \leftarrow x_i$
      for $\ell = 2$ **to** L **do**
        for each node j in layer ℓ **do**
          $in_j \leftarrow \sum_i w_{i,j}\, a_i$
          $a_j \leftarrow g(in_j)$
      / Propagate deltas backward from output layer to input layer */*
      for each node j in the output layer **do**
        $\Delta[j] \leftarrow g'(in_j) \times (y_j - a_j)$
      for $\ell = L - 1$ **to** 1 **do**
        for each node i in layer ℓ **do**
          $\Delta[i] \leftarrow g'(in_i) \sum_j w_{i,j}\, \Delta[j]$
      / Update every weight in network using deltas */*
      for each weight $w_{i,j}$ in *network* **do**
        $w_{i,j} \leftarrow w_{i,j} + \alpha \times a_i \times \Delta[j]$
  until some stopping criterion is satisfied
  return *network*

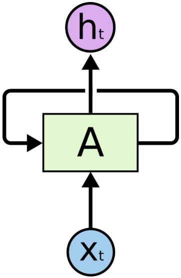
RECURRENT NEURAL NETWORKS

Various NN schemes



A Simple RNN Scheme

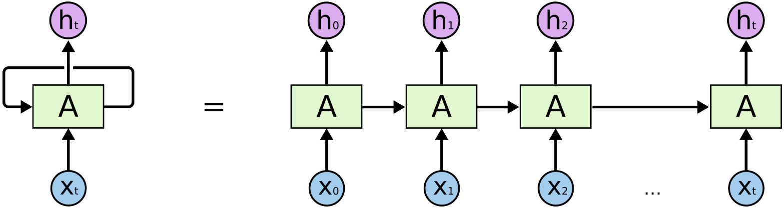
- Vanilla RNN is FFN with some self-referencing connections, feeding output back as part of the input
- A resulting crucial novel element is the time step label t, tracking RNN iterations



- X_t and h_t denote inputs and outputs *at the time* t, and A is the RNN chunk
- In this model we need to constantly feed the data into the network: data sequentiality

Unfolding RNN

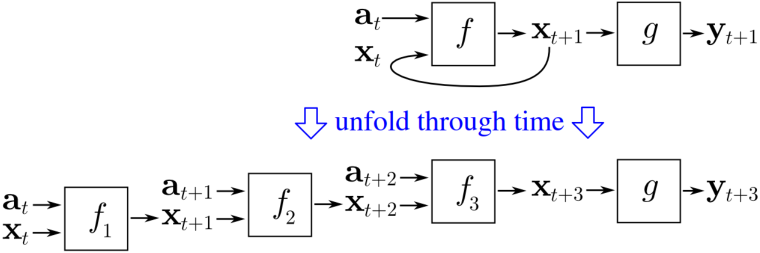
- RNN resembles more a temporal process than one-time operation
- A way to visualise the recurrent network functioning is to unfold it:



- In this form it starts resembling FFN, and one can apply backpropagation training

RNN Training

- RNN are trained upon unfonding k-times using the BPTT algorithm
- BackPropagation Through Time combines sequences of inputs $\{a_{n<t}\}$ and past outputs $\{x_{n<t}\}$ with the single expected output y_t for the time t

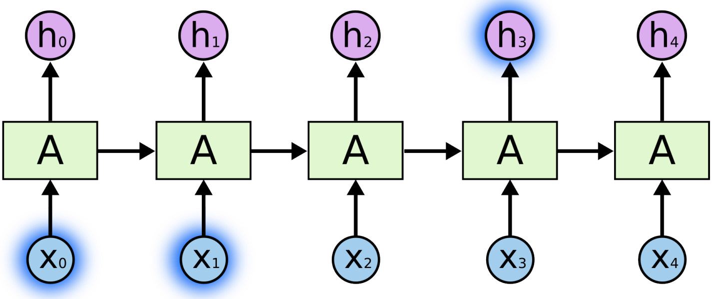


BPTT Pseudocode

```
Back_Propagation_Through_Time(a, y)   // a[t] is the input at time t. y[t] is the output
    Unfold the network to contain k instances of f
    do until stopping criteria is met:
        x = the zero-magnitude vector;// x is the current context
        for t from 0 to n - k         // t is time. n is the length of the training sequence
            Set the network inputs to x, a[t], a[t+1], ..., a[t+k-1]
            p = forward-propagate the inputs over the whole unfolded network
            e = y[t+k] - p;           // error = target - prediction
            Back-propagate the error, e, back across the whole unfolded network
            Sum the weight changes in the k instances of f together.
            Update all the weights in f and g.
            x = f(x, a[t]);           // compute the context for the next time-step
```

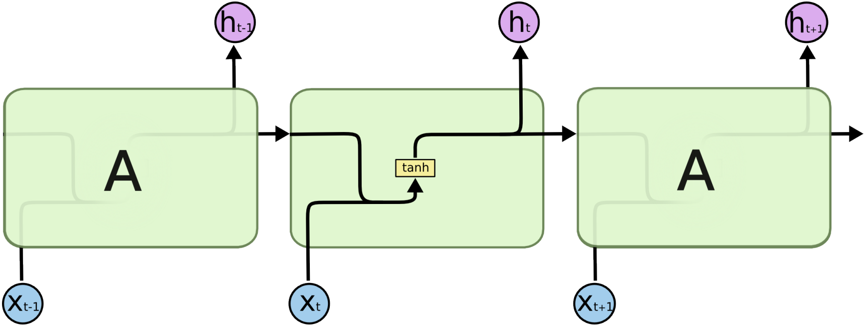
Context and Temporal Data Correlations

- RNN is capable of developing memory
- Its internal state is no longer specified by weights W alone
- Outputs at some future time step $t + k$ rely on the data at time t



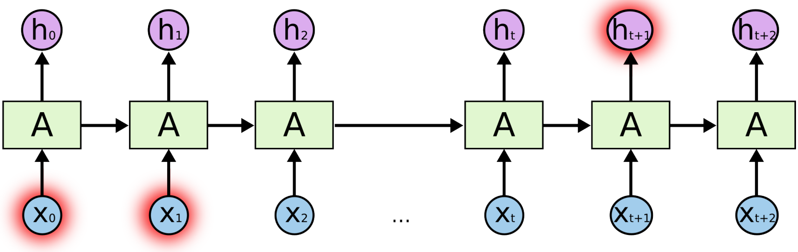
Example: a Simple RNN Sequence

- RNN with just a minimal modification of FF based on *tanh*() unit



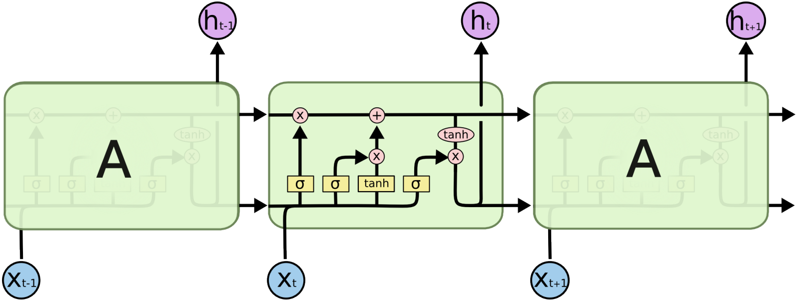
Vanishing Gradients Problem

- Upon multiple nestings sigmoid(-like) functions lead to exponential decay of error information
- Standard RNN loose the ability to learn long-term correlations



VGP Solution Strategy: Protect Unit Cell Data

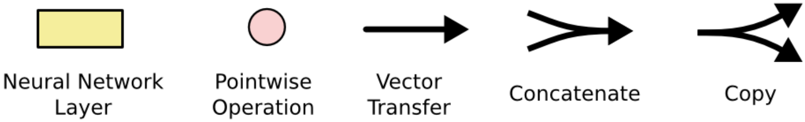
- LSTM breakthrough came from realising, that one can protect errors from rapid decay
- LSTM introduces *gated* networks, resembling circuits, but based on analog sigmoid and *tanh*() gates



- Such cells can be stacked to build a Deep RNN and lead to various architecture tillings

Circuit operations

- Data flow inside the cell is subject to several operations

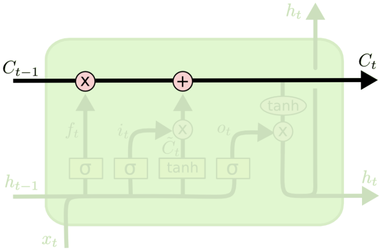


- Training is performed using BPTT and acts on parameters embedded in yellow gates σ and $tanh()$
- Red $tanh()$ gate squashes the data to $[-1, 1]$ before finally releasing it

HOW DOES IT WORK?

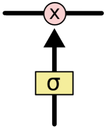
LSTM workflow: Memory

- The core component is the internal state C_i maintaining the memory
- It is subject to modifications resulting form the input and past processing outputs



LSTM workflow: Gates

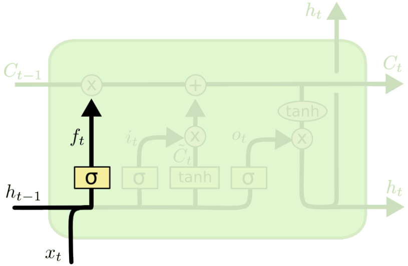
- The gate mechanism is governed with sigmoid functions: $1/(1 + exp(-t)$
- They assign fuzzy values from $[0, 1]$, deciding if information is to be blocked (~ 0) or transmitted (~ 1)



- Here upon weights assignment two vectors are Hadamard-multiplied (pointwise)

LSTM workflow: The Forget Gate

- The gate f_t decides if some data should be maintained or removed from the cell state

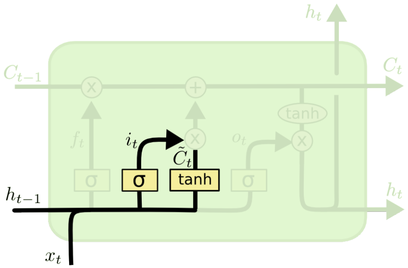


$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \ + \ b_f\right)$$

- The product will decrease the value of vector components in C_{t-1} multiplied by small σ results

LSTM workflow: The New State Gate

- This gate computes the new cell state candidate (it's the usual RNN unit action counterpart)



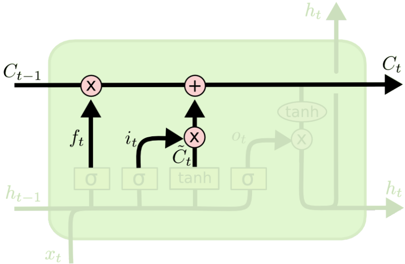
$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \ + \ b_i\right)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \ + \ b_C)$$

- The input gate i decides what data to update, and *tanh*() computes the new candidate $\tilde{C}$ based on the inputs x_t and the previous output h_{t-1}

LSTM workflow: The Cell Update Action

- The memory update combines forget and candidate actions to produce C_t

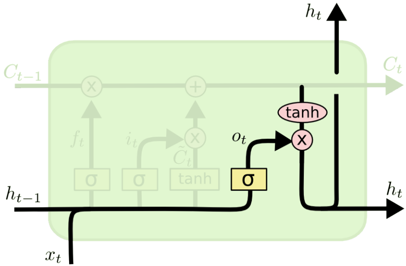


$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

- The essence of the LSTM idea is the central plus sign beyond the $\tilde{C}$ cell
- Here, unlike with the forget gate f_t, we *add* data, not multiply by a new one, and therefore preserve errors in the memory stream

LSTM workflow: The Output Gate

- The memory is released based on the output gate o_t decision (it is still preserved in C_t)

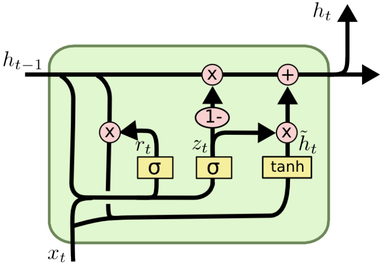


$$o_t = \sigma\left(W_o \left[h_{t-1}, x_t\right] + b_o\right)$$
$$h_t = o_t * \tanh\left(C_t\right)$$

- The output is normalised to the range $[-1, 1]$ by the *tanh*() gate and the cycle repeats

LSTM simplified: GRU

- There are many modifications of LSTM,
- A prominent one introduced in 2014 is the Gated Recurrent Unit combining some gates together
- There is however little difference in practical applications between them, with GRU being somewhat simpler to train

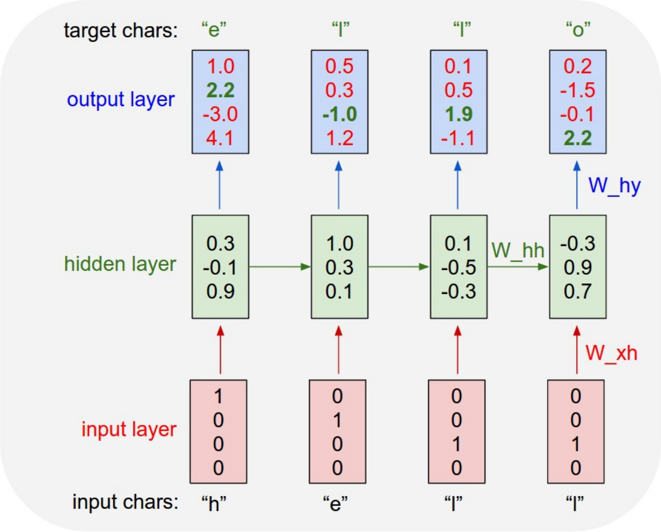


$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$
$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$
$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$
$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

LSTM application: text generation

- Imagine a large volume of text sharing some common features, e.g. same author
- Imagine a map between words or letters and numbers
- Train the LSTM/RNN on the text and teach it the large scale relations present in the data: its structure
- It appears, that by seeding the trained RNN one can generate texts!

LSTM text generator training



Other RNN applications

- Deep RNN were used in Tokamak instability forecasting
- Massive CUDA implementation works amazingly well, potentially solving major technical obstacle in fusion
- LSTM based human activity recognition: 91% accuracy https://github.com/guillaume-chevalier/LSTM-Human-Activity-Recognition
- ...

SUMMARY

Closing remarks

1. RNN resemble more a conscious thinking process than a one-time operation
2. RNN seem to have a huge potential and can simulate creativity
3. A major new idea in RNN is 'attention' - focusing on selected elements of the data under study
4. GPU, GPU, GPU!
5. We will be using LSTM for multimodal emotion recognition in video games at InnovationLab

References

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