

Deep Learning Reading Group

Sequence Modelling: Recurrent and Recursive Nets

Cameron Roach (PhD Candidate)

Monash University

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Introduction

Recurrent neural networks (RNNs) are used to process sequential data such as:

- ▶ time series
- ▶ natural language
- ▶ images.

RNNs are used to process a sequence of values $\mathbf{x}^{(1)}, \dots, \mathbf{x}^{(\tau)}$.

RNNs share parameters across the model. They do not require separate parameters at each time step which allows RNNs to generalize to different forms.

Examples

Time series forecasting

A recent kaggle competition forecasting daily hits on Wikipedia pages was won using a sequence to sequence network (Suilin 2017).

Natural language processing

An RNN trained off Wikipedia articles can learn interesting things about the structure of language.

Cell sensitive to position in line:

The sole importance of the crossing of the Berezina lies in the fact that it plainly and indubitably proved the fallacy of all the plans for cutting off the enemy's retreat and the soundness of the only possible line of action - the one Kutuzov and the general mass of the army demanded - namely, simply to follow the enemy up. The French crowd fled at a continually increasing speed and all its energy was directed to reaching its goal. It fled like a wounded animal and it was impossible to block its path. This was shown not so much by the arrangements it made for crossing as by what took place at the bridges. When the bridges broke down, unarmed soldiers, people from Moscow and women with children who were with the French transport, all - carried on by vis inertiae - pressed forward into boats and into the ice-covered water and did not, surrender.

Cell that turns on inside quotes:

"You mean to imply that I have nothing to eat out of.... On the contrary, I can supply you with everything even if you want to give dinner parties," warmly replied Chichagov, who tried by every word he spoke to prove his own rectitude and therefore imagined Kutuzov to be animated by the same desire.

Kutuzov, shrugging his shoulders, replied with his subtle penetrating smile: "I meant merely to say what I said."

Cell that robustly activates inside if statements:

```
static int __dequeue_signal(struct sigpending *pending, sigset_t *mask,
                           siginfo_t *info)
{
    int sig = next_signal(pending, mask);
    if (sig) {
        if (current->notifier) {
            if (sigismember(current->notifier_mask, sig)) {
                if (!current->notifier)(current->notifier_data)) {
                    clear_thread_flag(TIF_SIGPENDING);
                    return 0;
                }
            }
        }
        collect_signal(sig, pending, info);
    }
    return sig;
}
```

A large portion of cells are not easily interpretable. Here is a typical example:

```
/* Unpack a filter field's string representation from user-space
 * buffer. */
char *audit_unpack_string(void **bufp, size_t *remain, size_t len)
{
    char *str;
    if (!*bufp || (len == 0) || (len > *remain))
        return ERR_PTR(-EINVAL);
    /* Of the currently implemented string fields, PATH_MAX
     * defines the longest valid length.
     */
}
```

Figure 1: Text fed to an RNN trained off Wikipedia articles. Colour indicates activation of a neuron. The RNN has been able to learn some very interpretable algorithms. (Image: Karpathy (2016))

RNN architecture

Unfolding computational graphs

The hidden units of a RNN can be expressed in both folded and unfolded forms.

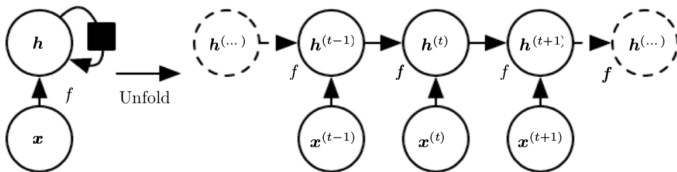


Figure 2: Folded and unfolded versions of a RNN with no outputs (Image: Goodfellow, Bengio, and Courville (2016))

We can express this as

$$\begin{aligned}\mathbf{h}^{(t)} &= \mathcal{G}^{(t)} \left(\mathbf{x}^{(t)}, \mathbf{x}^{(t-1)}, \dots, \mathbf{x}^{(1)} \right) \\ &= f \left(\mathbf{h}^{(t-1)}, \mathbf{x}^{(t)}; \boldsymbol{\theta} \right).\end{aligned}$$

Using the unfolded representation allows us to learn a single model f for all time steps.

RNN example

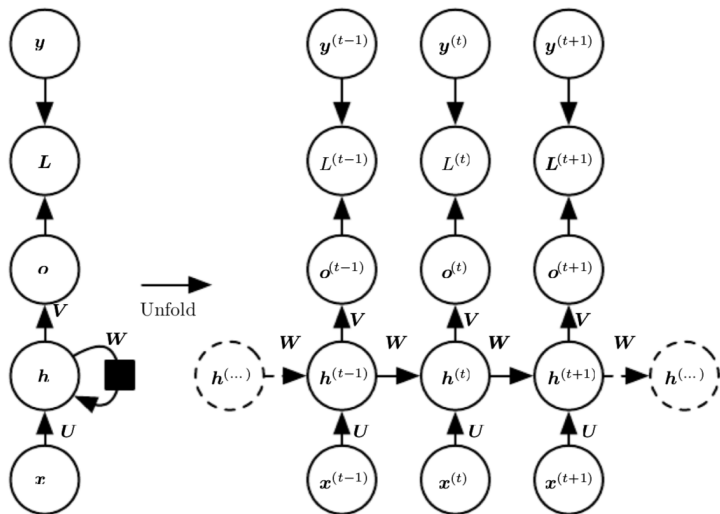


Figure 3: A simple RNN example. (Image: Goodfellow, Bengio, and Courville (2016))

Training RNNs

RNNs are trained using **back-propagation through time** (BPTT). BPTT is just standard back-propagation applied to the unfolded graph.

Teacher forcing is an alternative to BPTT and can be used when outputs connect back to the hidden units in the next step and there are no hidden-to-hidden connections. Teacher forcing uses the correct output $\mathbf{y}^{(t-1)}$ as the input to $\mathbf{h}^{(t)}$. This

- ▶ decouples the time steps
- ▶ allows for parallelisation.

Types of RNNs

There are many types of RNNs, such as:

- ▶ bidirectional
- ▶ encoder-decoder sequence-to-sequence architectures
- ▶ deep recurrent networks
- ▶ recursive neural networks.

Learning long term dependencies

Learning long term dependencies is difficult due to vanishing or exploding gradients. A simple recurrence relation illustrates why

$$\begin{aligned}\mathbf{h}^{(t)} &= \mathbf{W}'\mathbf{h}^{(t-1)} \\ &= (\mathbf{W}^t)' \mathbf{h}^{(0)} \\ &= \left[(\mathbf{Q}\mathbf{\Lambda}\mathbf{Q}')^t \right]' \mathbf{h}^{(0)} \\ &= \mathbf{Q}'\mathbf{\Lambda}^t\mathbf{Q}\mathbf{h}^{(0)}.\end{aligned}$$

where \mathbf{W} allows an eigendecomposition of the form used above and \mathbf{Q} is orthogonal.

Eigenvalues with magnitude less than one will disappear and those with magnitude greater than one will explode.

Long term dependencies can be handled with:

- ▶ Echo state networks
- ▶ Leaky units.

In practice the best results are achieved with gated RNNs (Goodfellow, Bengio, and Courville 2016) such as:

- ▶ Long short-term memory (LSTM) network
- ▶ Gated recurrent units (GRU).

LSTM

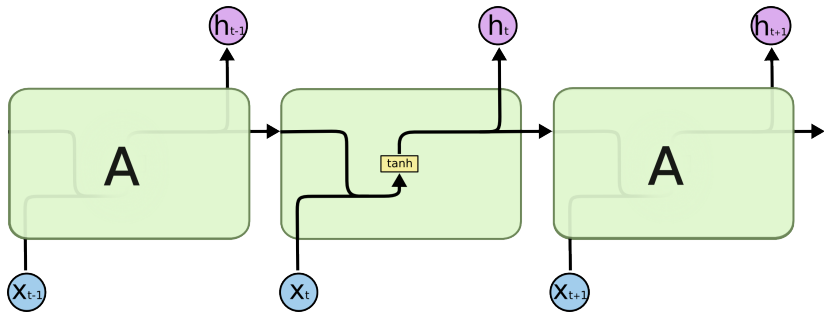


Figure 4: A standard RNN cell. (Image: Olah (2015))

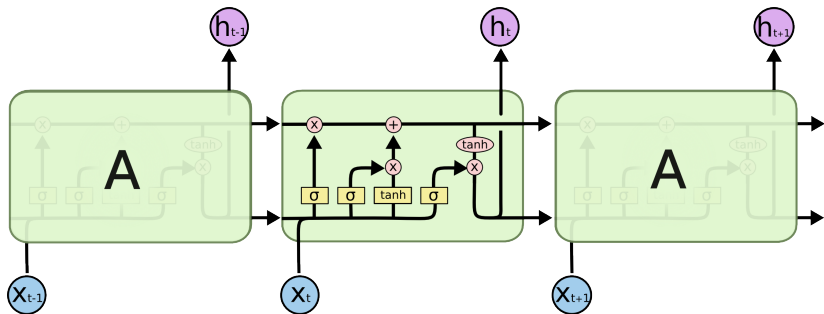


Figure 5: A LSTM cell. (Image: Olah (2015))

Optimisation for long term dependencies

RNNs suffer from exploding and vanishing gradients.

Exploding gradients can be handled with *gradient clipping*.

We can prevent vanishing gradients by constraining parameters to ensure the gradient vector $\nabla_{\mathbf{h}(t)} L$ being back-propagated maintains its magnitude. However, in practice LSTMs are more effective.

References

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