

# Gesture Recognition with Recurrent Neural Networks

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## Abstract

Gesture recognition is typically done through images, but it requires extensive effort to process image data into a form useful for gesture recognition. Our project uses accelerometer data from smartphones, so no special hardware is required. Recurrent neural networks provide a natural way to model time sequences, and the LSTM architecture in particular provides a way to model long-range dependencies that are prevalent in the gestures we tested. We implemented  $X$  gestures, and achieve an accuracy of  $X$  percent on the test set we generated.

## 1 Introduction

Intro goes here.

## 2 Data

We collected accelerometer data streamed from a smartphone.

## 3 Model

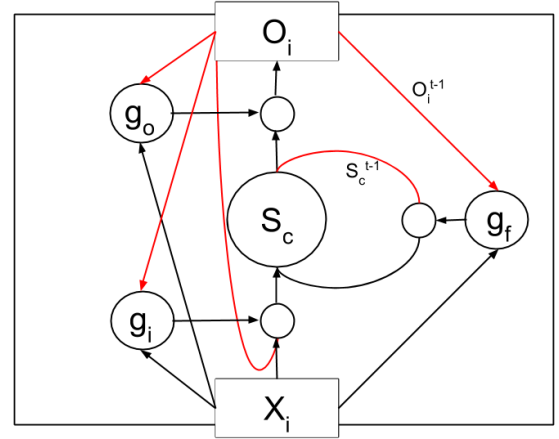
We implemented an LSTM (long short term memory) network based on the architectures proposed by Graves [1]. Specifically, our network contains the forget, input, and output gates, but lacks the peephole connections that connect the internal cell state to these gates (as done in Vinyals et al. [2]).

We then interleave layers of LSTM units with normal network layers to create a multilayer network.

### 3.1 Equations

We used squared error as our objective function.  $O$  is the network output and  $Y$  is the teacher value.  $n$  sums over each training example,  $t$  sums over

Figure 1: A single LSTM cell.



time, and  $i$  sums over the dimensions of each training example at a given timestep. Note that  $t$  varies with each training example.

$$L(Y, O) = \sum_n^N \sum_t^{\text{len}(O^n)} \sum_i^I \frac{1}{2} (o_i^{n,t} - y_i^{n,t})^2$$

Most of the equations on the forward and backward passes are the same as those in Graves [1], but some were missing so we specify all for completeness.

### 3.2 Forward Dynamics

The forward dynamics of the network are specified as follows. Equations are specified for a whole layer (rather than per unit). Bolded values represent vectors. Note that  $*$  represents a point-wise multiply.

Gates

$$\mathbf{a}_i = W_{i,x} \mathbf{x}^t + W_{i,o} \mathbf{o}^{t-1}$$

$$\mathbf{g}_i = \sigma(\mathbf{a}_i)$$

$$\mathbf{a}_f = W_{f,x} \mathbf{x}^t + W_{f,o} \mathbf{o}^{t-1}$$

$$\begin{aligned}\mathbf{g}_f &= \sigma(\mathbf{a}_f) \\ \mathbf{a}_o &= W_{o,x}\mathbf{x}^t + W_{o,o}\mathbf{o}^{t-1} \\ \mathbf{g}_o &= \sigma(\mathbf{a}_o)\end{aligned}$$

Cell State

$$\begin{aligned}\mathbf{a}_c &= W_{c,x}\mathbf{x}^t + W_{c,o}\mathbf{o}^{t-1} \\ \mathbf{s}_c &= \mathbf{g}_i * \sigma(\mathbf{a}_c) + \mathbf{g}_f * \mathbf{s}_c^{t-1}\end{aligned}$$

Cell Output (Hidden State)

$$\mathbf{o} = \mathbf{g}_i * \tanh(\mathbf{s}_c)$$

Normal Layer Output

$$\begin{aligned}\mathbf{a}_n &= W_n\mathbf{o} \\ \mathbf{n} &= \sigma(\mathbf{a}_n)\end{aligned}$$

### 3.3 Backpropagation

$\delta_k^{L+1}$  represents the error backpropogating from the above layer. As with before,  $*$  represents a pointwise multiplication.

Cell Output

$$\begin{aligned}\delta_n &= \delta_k^{L+1} * \tanh'(\mathbf{a}_n) \\ \delta_h &= W_{i,h}^T \delta_i^{t+1} + W_{f,h}^T \delta_f^{t+1} + W_{o,h}^T \delta_o^{t+1} + W_{c,h}^T \delta_s^{t+1} \\ \frac{\partial L}{\partial \mathbf{o}} &= W_n^T \delta_n + \delta_h\end{aligned}$$

Gates

$$\delta_o = \sigma'(\mathbf{a}_o) * \tanh(\mathbf{s}_c) * \frac{\partial L}{\partial \mathbf{o}}$$

BLAH

## 4 Training

We trained our network using BPTT (backpropogation through time) and gradient descent with momentum.

## 5 Decoding

## 6 Example L<sup>A</sup>T<sub>E</sub>Xstuff

- Item Example 1
- Item Example 2

Noindent

### 6.1 subsection

```
\usepackage{times}
\usepackage{latexsym}
```

“(Graves, 2008) Quote”

Column	Col	Col
row blah	blah	blah
row blah	blah	blah

Table 1: Example table!

## 6.2 Sections

**Citations:** Citations within the text appear in parentheses as (?) or, if the author’s name appears in the text itself, as Gusfield (?). Append lower-case letters to the year in cases of ambiguity. Treat double authors as in (?), but write as in (?) when more than two authors are involved. Collapse multiple citations as in (?; ?). Also refrain from using full citations as sentence constituents. We suggest that instead of

you use

“Gusfield (?) showed that ...”

If you are using the provided L<sup>A</sup>T<sub>E</sub>X and BibT<sub>E</sub>X style files, you can use the command `\newcite` to get “author (year)” citations.

As reviewing will be double-blind, the submitted version of the papers should not include the authors’ names and affiliations. Furthermore, self-references that reveal the author’s identity, e.g.,

“We previously showed (?) ...”

should be avoided. Instead, use citations such as

“Gusfield (?) previously showed ... ”

## 6.3 Footnotes

**Footnotes:** Put footnotes at the bottom of the page and use 9 points text. They may be numbered or referred to by asterisks or other symbols.<sup>1</sup> Footnotes should be separated from the text by a line.<sup>2</sup>

## Acknowledgments

Brian is our savior.

## References

- [1] Alex Graves. 2008. *Supervised Sequence Labelling with Recurrent Neural Networks*. PhD Thesis.
- [2] Oriol Vinyals, Alexander Toshev, Samy Bengio, Dumitru Erhan. 2014. *Show and Tell: A Neural Image Caption Generator*.

<sup>1</sup>This is how a footnote should appear.

<sup>2</sup>Note the line separating the footnotes from the text.