Understanding LSTM Networks

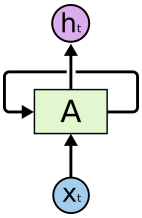
Posted on August 27, 2015

Recurrent Neural Networks

Humans don't start their thinking from scratch every second. As you read this essay, you understand each word based on your understanding of previous words. You don't throw everything away and start thinking from scratch again. Your thoughts have persistence.

Traditional neural networks can't do this, and it seems like a major shortcoming. For example, imagine you want to classify what kind of event is happening at every point in a movie. It's unclear how a traditional neural network could use its reasoning about previous events in the film to inform later ones.

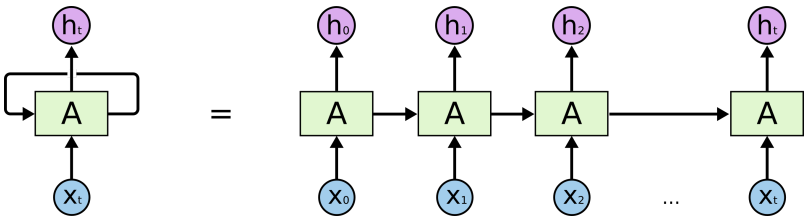
Recurrent neural networks address this issue. They are networks with loops in them, allowing information to persist.



Recurrent Neural Networks have loops.

In the above diagram, a chunk of neural network, A, looks at some input x_t and outputs a value h_t. A loop allows information to be passed from one step of the network to the next.

These loops make recurrent neural networks seem kind of mysterious. However, if you think a bit more, it turns out that they aren't all that different than a normal neural network. A recurrent neural network can be thought of as multiple copies of the same network, each passing a message to a successor. Consider what happens if we unroll the loop:



An unrolled recurrent neural network.

This chain-like nature reveals that recurrent neural networks are intimately related to sequences and lists. They're the natural architecture of neural network to use for such data.

And they certainly are used! In the last few years, there have been incredible success applying RNNs to a variety of problems: speech recognition, language modeling, translation, image captioning... The list goes on. I'll leave discussion of the amazing feats one can achieve with RNNs to Andrej Karpathy's excellent blog post, The Unreasonable Effectiveness of

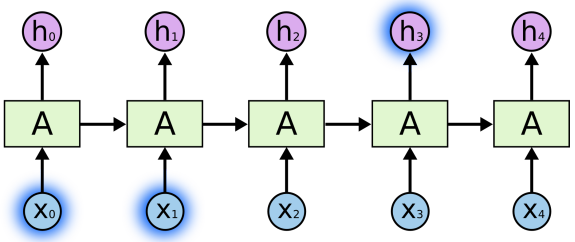
Recurrent Neural Networks (http://karpathy.github.io/2015/05/21/rnn-effectiveness/). But they really are pretty amazing.

Essential to these successes is the use of "LSTMs," a very special kind of recurrent neural network which works, for many tasks, much much better than the standard version. Almost all exciting results based on recurrent neural networks are achieved with them. It's these LSTMs that this essay will explore.

The Problem of Long-Term Dependencies

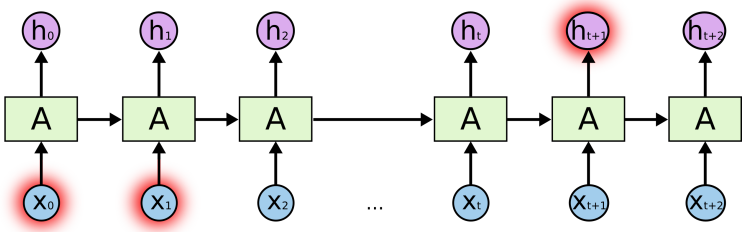
One of the appeals of RNNs is the idea that they might be able to connect previous information to the present task, such as using previous video frames might inform the understanding of the present frame. If RNNs could do this, they'd be extremely useful. But can they? It depends.

Sometimes, we only need to look at recent information to perform the present task. For example, consider a language model trying to predict the next word based on the previous ones. If we are trying to predict the last word in "the clouds are in the *sky*," we don't need any further context – it's pretty obvious the next word is going to be sky. In such cases, where the gap between the relevant information and the place that it's needed is small, RNNs can learn to use the past information.



But there are also cases where we need more context. Consider trying to predict the last word in the text "I grew up in France... I speak fluent *French*." Recent information suggests that the next word is probably the name of a language, but if we want to narrow down which language, we need the context of France, from further back. It's entirely possible for the gap between the relevant information and the point where it is needed to become very large.

Unfortunately, as that gap grows, RNNs become unable to learn to connect the information.



In theory, RNNs are absolutely capable of handling such "long-term dependencies." A human could carefully pick parameters for them to solve toy problems of this form. Sadly, in practice, RNNs don't seem to be able to learn them. The problem was explored in depth by Hochreiter (1991) [German] (http://people.idsia.ch/~juergen/SeppHochreiter1991ThesisAdvisorSchmidhuber.pdf) and Bengio, et al. (1994) (http://www-dsi.ing.unifi.it/~paolo/ps/tnn-94-gradient.pdf), who found some pretty fundamental reasons why it might be difficult.

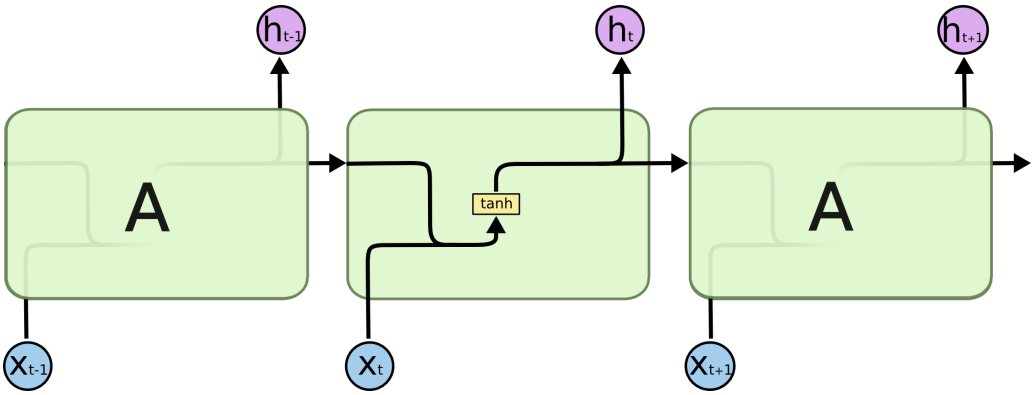
Thankfully, LSTMs don't have this problem!

LSTM Networks

Long Short Term Memory networks – usually just called "LSTMs" – are a special kind of RNN, capable of learning long-term dependencies. They were introduced by Hochreiter & Schmidhuber (1997) (http://deeplearning.cs.cmu.edu/pdfs/Hochreiter97_lstm.pdf), and were refined and popularized by many people in following work.[1] They work tremendously well on a large variety of problems, and are now widely used.

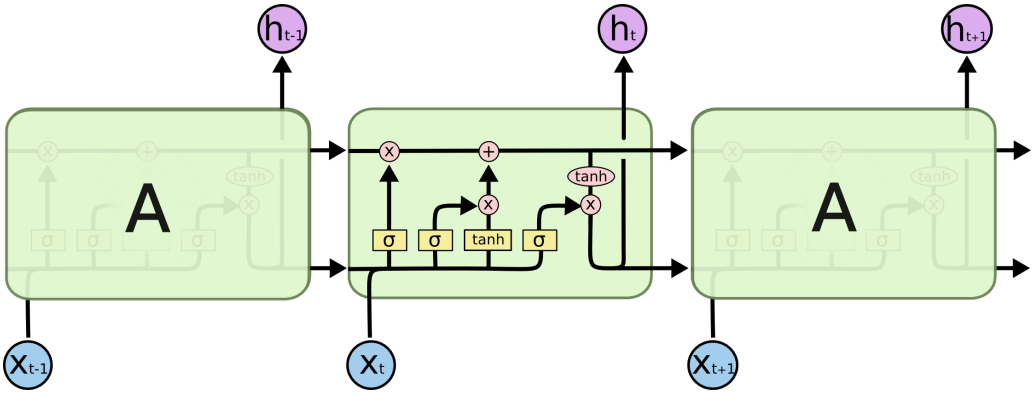
LSTMs are explicitly designed to avoid the long-term dependency problem. Remembering information for long periods of time is practically their default behavior, not something they struggle to learn!

All recurrent neural networks have the form of a chain of repeating modules of neural network. In standard RNNs, this repeating module will have a very simple structure, such as a single tanh layer.



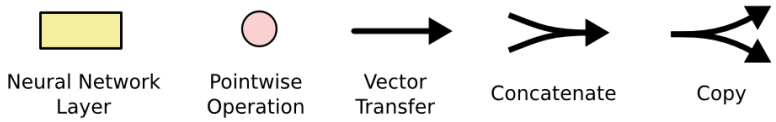
The repeating module in a standard RNN contains a single layer.

LSTMs also have this chain like structure, but the repeating module has a different structure. Instead of having a single neural network layer, there are four, interacting in a very special way.



The repeating module in an LSTM contains four interacting layers.

Don't worry about the details of what's going on. We'll walk through the LSTM diagram step by step later. For now, let's just try to get comfortable with the notation we'll be using.

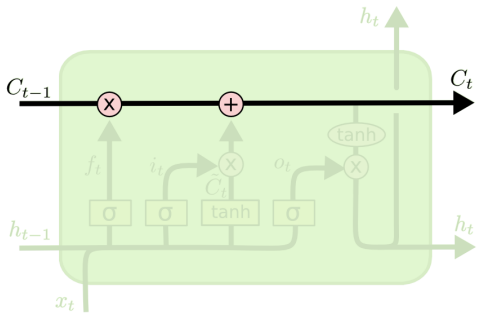


In the above diagram, each line carries an entire vector, from the output of one node to the inputs of others. The pink circles represent pointwise operations, like vector addition, while the yellow boxes are learned neural network layers. Lines merging denote concatenation, while a line forking denote its content being copied and the copies going to different locations.

The Core Idea Behind LSTMs

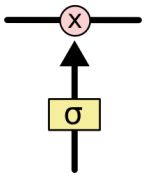
The key to LSTMs is the cell state, the horizontal line running through the top of the diagram.

The cell state is kind of like a conveyor belt. It runs straight down the entire chain, with only some minor linear interactions. It's very easy for information to just flow along it unchanged.



The LSTM does have the ability to remove or add information to the cell state, carefully regulated by structures called gates.

Gates are a way to optionally let information through. They are composed out of a sigmoid neural net layer and a pointwise multiplication operation.



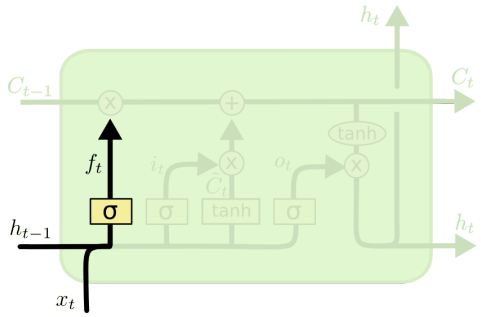
The sigmoid layer outputs numbers between zero and one, describing how much of each component should be let through. A value of zero means "let nothing through," while a value of one means "let everything through!"

An LSTM has three of these gates, to protect and control the cell state.

Step-by-Step LSTM Walk Through

The first step in our LSTM is to decide what information we're going to throw away from the cell state. This decision is made by a sigmoid layer called the "forget gate layer." It looks at h_{t-1} and x_t, and outputs a number between 0 and 1 for each number in the cell state C_{t-1}. A 1 represents "completely keep this" while a 0 represents "completely get rid of this."

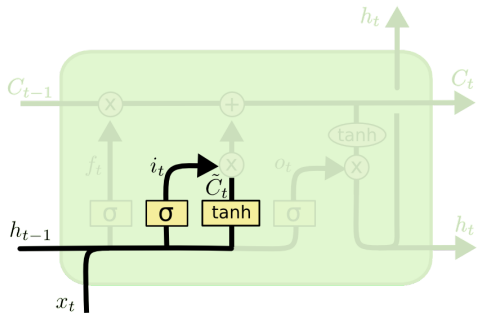
Let's go back to our example of a language model trying to predict the next word based on all the previous ones. In such a problem, the cell state might include the gender of the present subject, so that the correct pronouns can be used. When we see a new subject, we want to forget the gender of the old subject.



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

The next step is to decide what new information we're going to store in the cell state. This has two parts. First, a sigmoid layer called the "input gate layer" decides which values we'll update. Next, a tanh layer creates a vector of new candidate values, $\tilde{C}_t$, that could be added to the state. In the next step, we'll combine these two to create an update to the state.

In the example of our language model, we'd want to add the gender of the new subject to the cell state, to replace the old one we're forgetting.

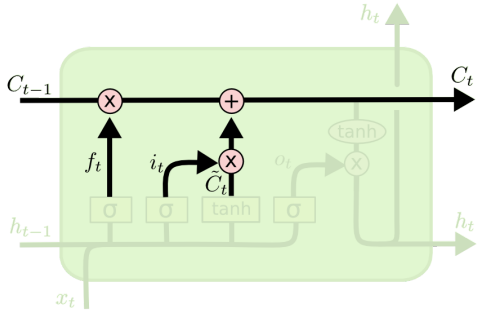


$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \; + \; b_i\right)$$
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \; + \; b_C)$$

It's now time to update the old cell state, C_{t-1}, into the new cell state C_t. The previous steps already decided what to do, we just need to actually do it.

We multiply the old state by f_t, forgetting the things we decided to forget earlier. Then we add $i_t * \tilde{C}_t$. This is the new candidate values, scaled by how much we decided to update each state value.

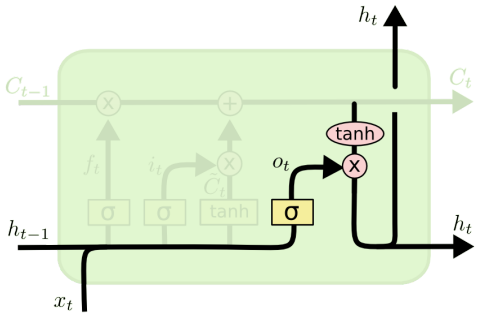
In the case of the language model, this is where we'd actually drop the information about the old subject's gender and add the new information, as we decided in the previous steps.



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

Finally, we need to decide what we're going to output. This output will be based on our cell state, but will be a filtered version. First, we run a sigmoid layer which decides what parts of the cell state we're going to output. Then, we put the cell state through tanh (to push the values to be between -1 and 1) and multiply it by the output of the sigmoid gate, so that we only output the parts we decided to.

For the language model example, since it just saw a subject, it might want to output information relevant to a verb, in case that's what is coming next. For example, it might output whether the subject is singular or plural, so that we know what form a verb should be conjugated into if that's what follows next.

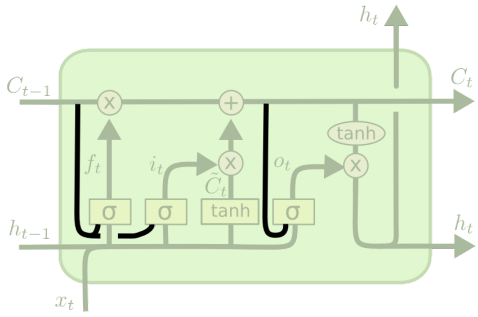


$$o_t = \sigma\left(W_o \left[h_{t-1}, x_t\right] + b_o\right)$$
$$h_t = o_t * \tanh\left(C_t\right)$$

Variants on Long Short Term Memory

What I've described so far is a pretty normal LSTM. But not all LSTMs are the same as the above. In fact, it seems like almost every paper involving LSTMs uses a slightly different version. The differences are minor, but it's worth mentioning some of them.

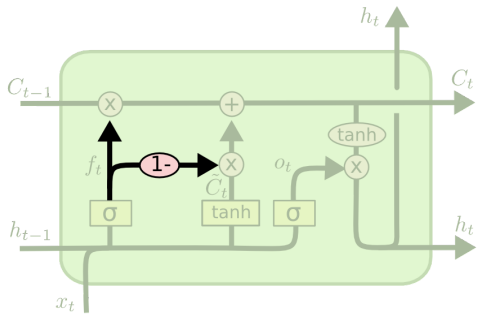
One popular LSTM variant, introduced by Gers & Schmidhuber (2000) (ftp://ftp.idsia.ch/pub/juergen/TimeCount-IJCNN2000.pdf), is adding "peephole connections." This means that we let the gate layers look at the cell state.



$$f_t = \sigma\left(W_f \cdot [\boldsymbol{C_{t-1}}, h_{t-1}, x_t] + b_f\right)$$
$$i_t = \sigma\left(W_i \cdot [\boldsymbol{C_{t-1}}, h_{t-1}, x_t] + b_i\right)$$
$$o_t = \sigma\left(W_o \cdot [\boldsymbol{C_t}, h_{t-1}, x_t] + b_o\right)$$

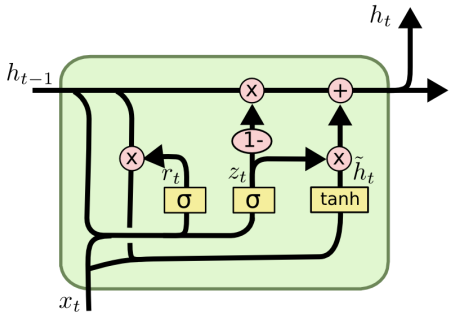
The above diagram adds peepholes to all the gates, but many papers will give some peepholes and not others.

Another variation is to use coupled forget and input gates. Instead of separately deciding what to forget and what we should add new information to, we make those decisions together. We only forget when we're going to input something in its place. We only input new values to the state when we forget something older.



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

A slightly more dramatic variation on the LSTM is the Gated Recurrent Unit, or GRU, introduced by Cho, et al. (2014) (http://arxiv.org/pdf/1406.1078v3.pdf). It combines the forget and input gates into a single "update gate." It also merges the cell state and hidden state, and makes some other changes. The resulting model is simpler than standard LSTM models, and has been growing increasingly popular.



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

These are only a few of the most notable LSTM variants. There are lots of others, like Depth Gated RNNs by Yao, et al. (2015) (http://arxiv.org/pdf/1508.03790v2.pdf). There's also some completely different approach to tackling long-term dependencies, like Clockwork RNNs by Koutnik, et al. (2014) (http://arxiv.org/pdf/1402.3511v1.pdf).

Which of these variants is best? Do the differences matter? Greff, et al. (2015) (http://arxiv.org/pdf/1503.04069.pdf) do a nice comparison of popular variants, finding that they're all about the same. Jozefowicz, et al. (2015) (http://jmlr.org/proceedings/papers/v37/jozefowicz15.pdf) tested more than ten thousand RNN architectures, finding some that worked better than LSTMs on certain tasks.

Conclusion

Earlier, I mentioned the remarkable results people are achieving with RNNs. Essentially all of these are achieved using LSTMs. They really work a lot better for most tasks!

Written down as a set of equations, LSTMs look pretty intimidating. Hopefully, walking through them step by step in this essay has made them a bit more approachable.

LSTMs were a big step in what we can accomplish with RNNs. It's natural to wonder: is there another big step? A common opinion among researchers is: "Yes! There is a next step and it's attention!" The idea is to let every step of an RNN pick information to look at from some larger collection of information. For example, if you are using an RNN to create a caption describing an image, it might pick a part of the image to look at for every word it outputs. In fact, Xu, *et al.* (2015) (http://arxiv.org/pdf/1502.03044v2.pdf) do exactly this – it might be a fun starting point if you want to explore attention! There's been a number of really exciting results using attention, and it seems like a lot more are around the corner...

Attention isn't the only exciting thread in RNN research. For example, Grid LSTMs by Kalchbrenner, *et al.* (2015) (http://arxiv.org/pdf/1507.01526v1.pdf) seem extremely promising. Work using RNNs in generative models – such as Gregor, *et al.* (2015) (http://arxiv.org/pdf/1502.04623.pdf), Chung, *et al.* (2015) (http://arxiv.org/pdf/1506.02216v3.pdf), or Bayer & Osendorfer (2015) (http://arxiv.org/pdf/1411.7610v3.pdf) – also seems very interesting. The last few years have been an exciting time for recurrent neural networks, and the coming ones promise to only be more so!

Acknowledgments

I'm grateful to a number of people for helping me better understand LSTMs, commenting on the visualizations, and providing feedback on this post.

I'm very grateful to my colleagues at Google for their helpful feedback, especially Oriol Vinyals (http://research.google.com/pubs/OriolVinyals.html), Greg Corrado (http://research.google.com/pubs/GregCorrado.html), Jon Shlens (http://research.google.com/pubs/JonathonShlens.html), Luke Vilnis (http://people.cs.umass.edu/~luke/), and Ilya Sutskever (http://www.cs.toronto.edu/~ilya/). I'm also thankful to many other friends and colleagues for taking the time to help me, including Dario Amodei (https://www.linkedin.com/pub/dario-amodei/4/493/393), and Jacob Steinhardt (http://cs.stanford.edu/~jsteinhardt/). I'm especially thankful to Kyunghyun Cho (http://www.kyunghyuncho.me/) for extremely thoughtful correspondence about my diagrams.

Before this post, I practiced explaining LSTMs during two seminar series I taught on neural networks. Thanks to everyone who participated in those for their patience with me, and for their feedback.

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1. In addition to the original authors, a lot of people contributed to the modern LSTM. A non-comprehensive list is: Felix Gers, Fred Cummins, Santiago Fernandez, Justin Bayer, Daan Wierstra, Julian Togelius, Faustian Gomez, Matteo Gagliolo, and Alex Graves (https://scholar.google.com/citations?user=DaFHynwAAAAJ&hl=en).↩

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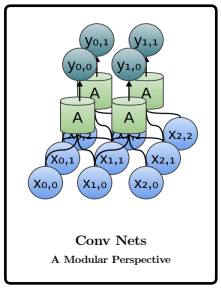

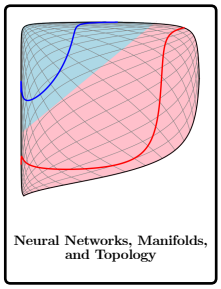

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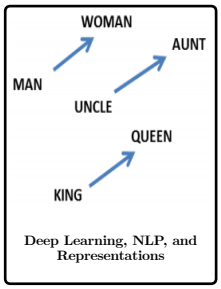

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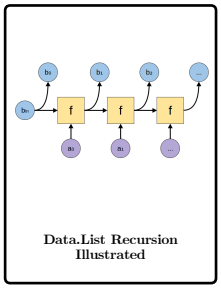

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Dan Quang • a year ago

Thank you! I've been trying to understand LSTM for a long time! This made it very clear :)

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> **chrisolah** Mod → Dan Quang • a year ago
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li kai • a year ago

Great!Great!Great!Great!Great!Great!Great!Great!Great!Great!

Much better than Alex Graves's paper!!!!

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> **Daniel Bigham** → li kai • 10 months ago
>
> LOL. I was just reading Alex Grave's paper and started to frown with the lack of explanation on the core LSTM idea. I googled, found this article, and your comment was at the top. Hilarious.
>
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Brandon Rohrer • 8 months ago

Thank you for the clear explanation! It's a rare that someone both has the ability to write so clearly and takes the time to do so. Your work is a gift to the rest of us.

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Alex Sosnovshchenko • 10 months ago

I made Russian translation of this excellent post, I hope you will not mind.
http://alexsosn.github.io/ml/2...

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> **bobriakov** → Alex Sosnovshchenko • 7 months ago
>
> Спасибо!
>
> 1 ▲ | ▼ • Reply • Share ›
>
> **chrisolah** Mod → Alex Sosnovshchenko • 10 months ago
>
> That looks lovely, Alex! Thanks for the translation!
>
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Steven Tang • a year ago

Great post! I am a little confused by the output h_t portion of the lstm.

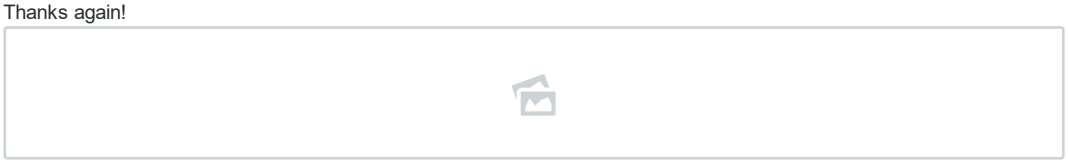
It looks like the dimension of C_t should be the number of dimensions in h_t-1 and x_t combined.

It also looks like h_t should be the dimension of C_t.

Obviously, my understanding can't be correct, or else the dimensionsality of h_t would grow by the dimensions of x_t at

every time step. Is there a mistake in my understanding somewhere? Is the output of h_t only the dimension of h_t-1, and NOT C_t?

Thanks again!



2 • Reply • Share ›

Atcold ➚ Steven Tang • a year ago

h_t, C_t and \tilde{C}_t share the same dimensionality.
The size of \tilde{C}_t comes directly from the 'hight' of W_C matrix (check \tilde{C}_t definition, above). W_C's 'width' is instead equal to size(h_t) + size(x_t).

2 • Reply • Share ›

Majid al-Dosari ➚ Atcold • 9 months ago

i don't get it. everything that's not a weight matrix is a vector of the same dimension. i don't get what you mean by this concatenation thing mathematically W_C[h_(t-1),x_t]. it seems unconventional.

do you mean 'wide' matrix times 'tall' vector b/c you put h and x on top of each other?? that would equal a tall vector which can't be right. it can't be two vectors side by side b/c then the result would be a matrix.

in the literature the weight matrix is separated out for each vector.

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chrisolah Mod ➚ Majid al-Dosari • 9 months ago

Here's a figure I made for the post but didn't include in the final version, which may help:

3 • Reply • Share ›

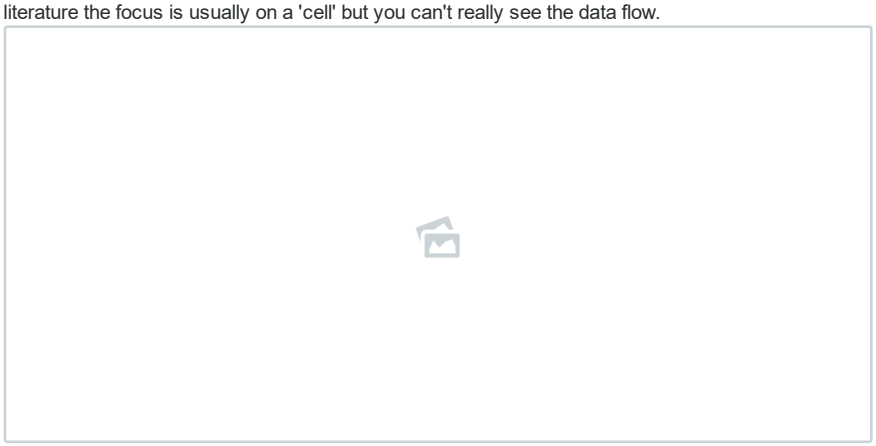
hughperkins ➚ chrisolah • 8 months ago

These diagrams look really nice. What are you using to draw them?

5 • Reply • Share ›

Majid al-Dosari ➚ chrisolah • 9 months ago

thx. i made a figure similar to yours actually (might need some more arrows) it's funny how in the literature the focus is usually on a 'cell' but you can't really see the data flow.



Reply • Share ›

chrisolah Mod ➚ Majid al-Dosari • 8 months ago
Nice! :)
Reply • Share ›

Ibrahim Sobh ➚ Majid al-Dosari • 3 months ago
please have a look at:
http://jmlr.org/proceedings/pa...
Reply • Share ›

Majid al-Dosari ➚ Majid al-Dosari • 9 months ago
oh i get it... two vectors on top of each other and height of W is size of vector.
Reply • Share ›

Atcold ➚ Majid al-Dosari • 9 months ago
Exactly. Ax + By = [A|B][x/y], where | concatenates horizontally and / vertically.
Reply • Share ›

Steven Tang ➚ Atcold • a year ago
Great, thanks for the explanation!
Reply • Share ›

Steven Yin • a year ago
Great post! Seems like RNN is great at predicting stuff. I am trying to see if RNN can be applied to time series classification. Do you have any papers you would suggest relating to that? Or are there any other types of Neural nets that are good at time series classification?
2 Reply • Share ›

Bryan Baek • a month ago
Really nice explanation about the LSTM. I was confused a lot but I just got quite better understanding.
Thanks a lot!
1 Reply • Share ›

Beheen Trimble • a month ago
Thank you.
1 Reply • Share ›

Weijie Huang • 8 months ago
In fact, how to calculate the "Wf [H t-1, X t]"? Is it the same as (Wf1*Ht-1 + Wf2*Xt)?
1 Reply • Share ›

gaurav gupta ➚ Weijie Huang • 4 days ago
I think they are same. h_t-1 is stacked on the top of x_t to form a single vertical one D vector. Let the total height be N. So Wf is a matrix of height N and width M.So Wf.[h_t-1/x_t]===> [M x N][N x 1] gives [M x1] . this the dimension of C_t.
Reply • Share ›

Ibrahim Sobh ➚ Weijie Huang • 3 months ago
I have the same question, do you have an answer?

please have a look at:
http://jmlr.org/proceedings/pa...
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Ghislain Gagne • 9 months ago

Excellent post, it made me understand better the inner workings of LSTM networks. Are LSTM nets suitable for time series prediction?
thanks
1 • Reply • Share ›

Rafael Espericueta ↗ Ghislain Gagne • 2 months ago
That's what LSTMs are for.
• Reply • Share ›

David Krueger • a year ago
Anyone's thoughts on IRNNs?

http://arxiv.org/pdf/1504.0094...
1 • Reply • Share ›

Anshul Mittal ↗ David Krueger • 9 months ago
Can you specify exactly what you wanna ask?
• Reply • Share ›

Jerry ↗ Anshul Mittal • 9 months ago
anshul mittal greatest FAC of all time
• Reply • Share ›

Zachary Jablons • a year ago
Excellent post!

I found the GRU diagram a bit hard to follow, I think it could be improved a bit by adding the equation labels.
1 • Reply • Share ›

chrisolah Mod ↗ Zachary Jablons • a year ago
I've added the labels -- thanks for pointing that out!
• Reply • Share ›

Gilles Daquin • 10 days ago
Why does it have to be so clear now! It's been bordering the mysterious to opaque until your super article.

Thanks a lot!
• Reply • Share ›

UserOne • 22 days ago
Can you speak on how Layer Normalization vs LSTM DropOut vs Recurrent Batch Normalization vs L1/L2 Regularization act as regularization tools to prevent over-fitting and which provide the best results in a LSTM network.
• Reply • Share ›

Sebastian Nickel • 24 days ago
While the diagrams look great, I find the equations a lot easier to understand :) I suppose I'm in a minority here.

Thank you so much for all these awesome essays.
• Reply • Share ›

Sergio Tudor • a month ago
Hi Chris, I loved it. Thank you!
Could you please help me grasp the meaning behind the following claim :

"LSTMs do not offer the correspondence that RNN unfolded in time do
(the mutual transferability, between equations and architectures). "

The only devil's advocate study I was able to find belongs to Zachary C. Liptonand John Berkowitz - "Critical Review of Recurrent Neural Networks for Sequence Learning "

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Vignesh • 2 months ago

Thanks for the post! I was wondering how the context of the future part can be accounted here. Say, in the example of language modelling, what if the current prediction depends on the future words. Is there anything like bidirectional connection? Thanks again

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> **Carl Thomé** → Vignesh • 2 months ago
>
> Yes, bidirectional LSTMs are common. It's typically just a matter of doing the exact same mathematical operations but first flipping the sequences so they are reversed. See this Keras example, for example: https://github.com/fchollet/ke...
>
> Reply • Share ›
>
> > **Vignesh** → Carl Thomé • 2 months ago
> >
> > Thanks Carl!
> >
> > Reply • Share ›

hstrobelt • 2 months ago

Thank you, very much. Your blog helped me a lot during the development of LSTMVis.

Reply • Share ›

Bayram Boyraz • 2 months ago

Hi, thanks for the post. I still have something unclear in my mind though. It looks like there is no output layer is there? h value of a memory cell is considered to be output? Not that h values from several memory cells are multiplied to some weights to have output layer values, right?

If this is the case, let's say that I would like to have a network with 2 input, 3 memory cells and I want my network to output only 1 value at each time stamp. If I should use h value of memory cell as an output, then the network will have to output 3 values at each time stamp, whereas I only wanted to have 1.

What about if I want to have 5 output neuron, meaning 5 output values at each time stamp? Then I will need to have at least 5 memory cells right?

I hope my question is clear. Thanks again for the explanatory post.

Reply • Share ›

skywalkerytx • 2 months ago

What will [H_{t-1},X_t] looks like? For example, If H_{t-1} = [[1,2][3,4]] and X_t = [5,6], is [H_{t-1},X_t] = [[1,2,5][3,4,6]]?

Reply • Share ›

Ben P • 2 months ago

would this work with the NEAT (Evolving Neural Networks through Augmenting Topologies) algorithm?

Reply • Share ›

aephi • 3 months ago

The clarity of this article is as beautiful as the diagrams. Helped me a lot.

Reply • Share ›

Ibrahim Sobh • 3 months ago

Thank you very much

Regarding LSTM, I have seen another implementation, for example the ft is:
ft = sgm(Wx xt + Wh hti-1 + bf)
Note that using 2 diferent W's, one for input x and the other for hidden state

Note that using 2 different W's, one for input x and the other for hidden state
ref: file:///C:/Users/Ibrahim/Desktop/jozefowicz15.pdf

While your version is:
ft = sgm (Wf.[ht-1,xt])
Note: using only one W that applied on the concatenated ht-1 and xt

What is the difference between the two versions? what are the dimensions of Wx, Wh and Wf?

Thank you

▲ | ▼ • Reply • Share ›

a52 • 3 months ago

I haven't taken the time yet to fully understand this (though this is much more helpful than Wikipedia's LSTM article), but I have a few questions.

Can an LSTM NN self-improve, based on new input? Does it have to learn through a genetic algorithm, or does it do everything by itself?

And what's the advantage of using this over something like a modified Markov chain? Is it that it (in the case of a language model) considers the whole sentence, not just the previous word? Are ordinary RNNs any different from a Markov chain?

Anyway, this article was very helpful, especially the diagrams.

Edit: I've done some more research, and I get it now.

▲ | ▼ • Reply • Share ›

Slawek Smyl • 3 months ago

Beautiful graphs! Would you mind if I used them in a conference paper? I would of course acknowledge you as an author.

▲ | ▼ • Reply • Share ›

Danijar • 4 months ago

Thanks for the great article. I'd like to add that in an LSTM layer with more than one cell, all the cell outputs h_t feed back into all the cell inputs. The incoming arrow labelled h_(t-1) can be a bit misleading since it looks like each cell only feeds back into itself. Schmidhuber has a nice slide on how multiple LSTM cells are connected: http://people.idsia.ch/~juerge...

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