

Understanding LSTM Networks

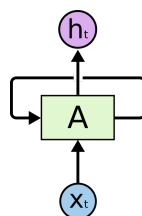
Posted on August 27, 2015

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.

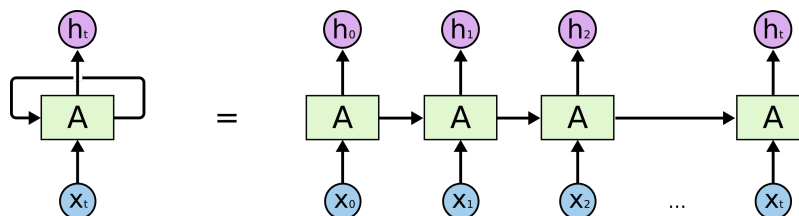
Recurrent neural networks address this issue. They are networks with loops in them, allowing information to persist.



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

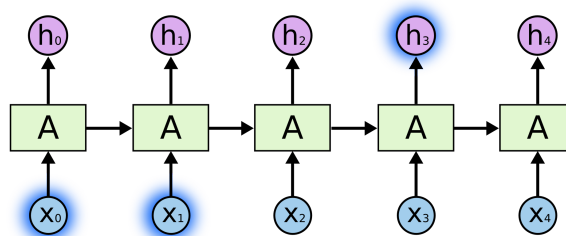
Recurrent Neural Networks (<http://karpathy.github.io/2015/05/21/rnn-effectiveness/>). But they really are pretty amazing.

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

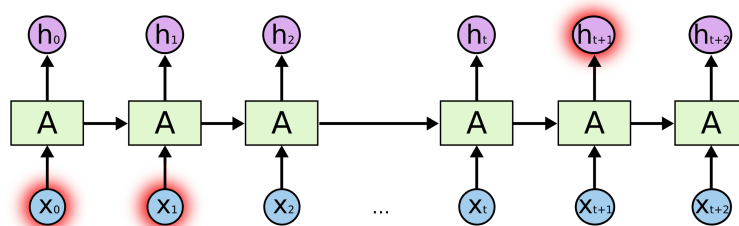
One of the appeals of RNNs is the idea that they might be able to connect previous information to the present task, such as using previous video frames might inform the understanding of the present frame. If RNNs could do this, they’d be extremely useful. But can they? It depends.

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.

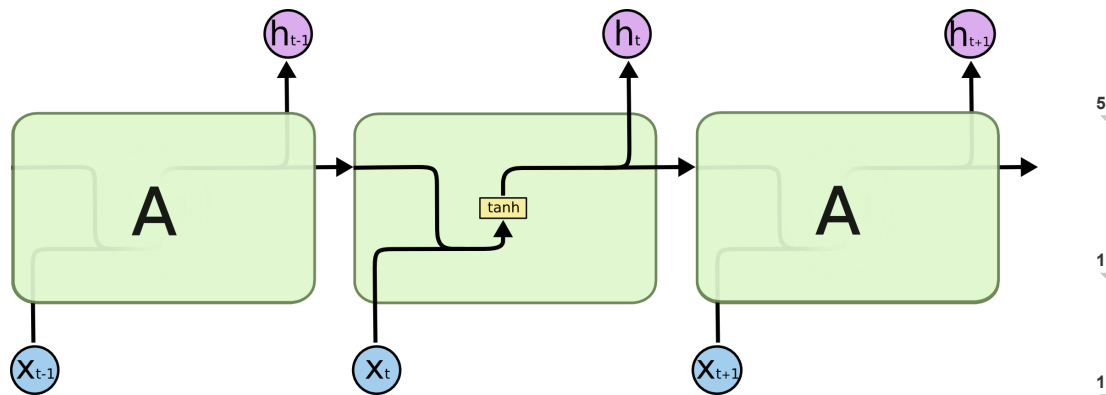
Thankfully, LSTMs don’t have this problem!

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.

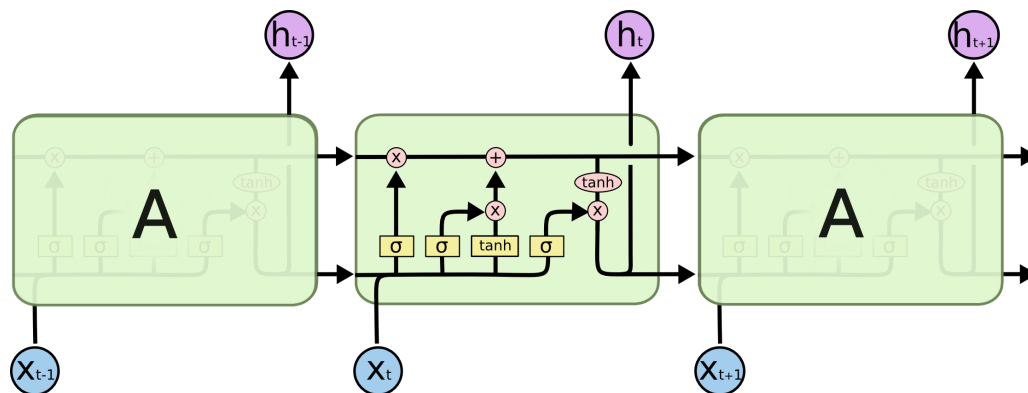
LSTMs are explicitly designed to avoid the long-term dependency problem. Remembering information for long periods of time is practically their default behavior, not something they struggle to learn!

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.



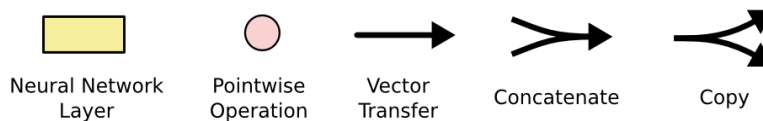
The repeating module in a standard RNN contains a single layer.

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 denotes its content being copied and the copies going to different locations.

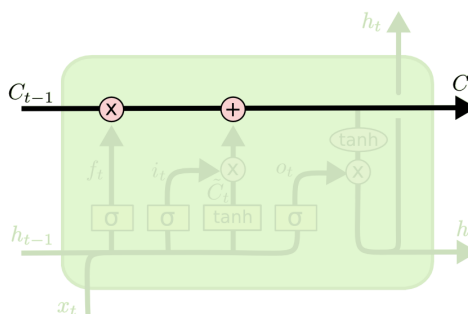
255

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.

255

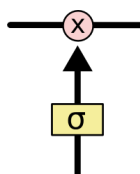


1

2

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!"

1

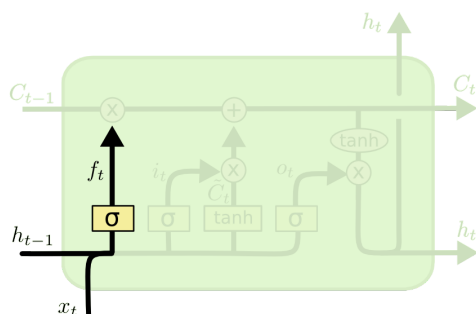
An LSTM has three of these gates, to protect and control the cell state.

3

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."

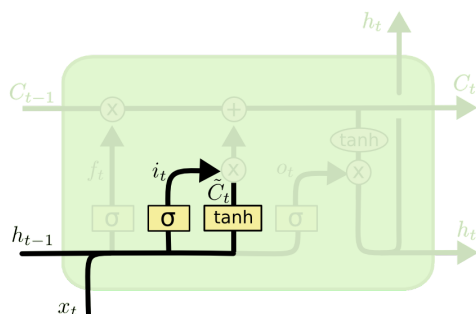
Let's go back to our example of a language model trying to predict the next word based on all the previous ones. In such a problem, the cell state might include the gender of the present subject, so that the correct pronouns can be used. When we see a new subject, we want to forget the gender of the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



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

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.



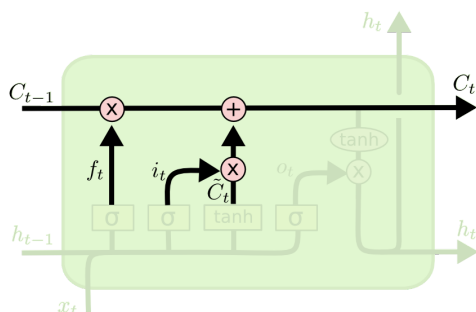
$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

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

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.

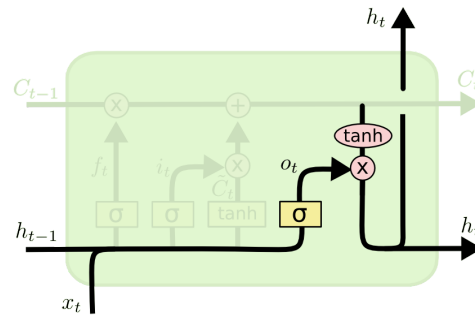
In the case of the language model, this is where we'd actually drop the information about the old subject's gender and add the new information, as we decided in the previous steps.



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

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.



$$o_t = \sigma(W_o [h_{t-1}, x_t] + b_o)$$

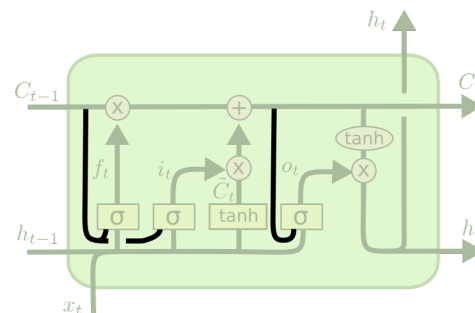
$$h_t = o_t * \tanh(C_t)$$

1

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-LJCNN2000.pdf>), is adding "peephole connections." This means that we let the gate layers look at the cell state.



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

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

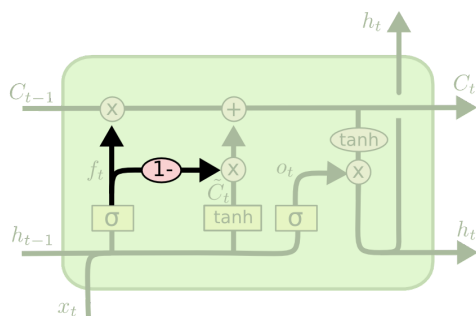
$$o_t = \sigma(W_o \cdot [C_t, h_{t-1}, x_t] + b_o)$$

1

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

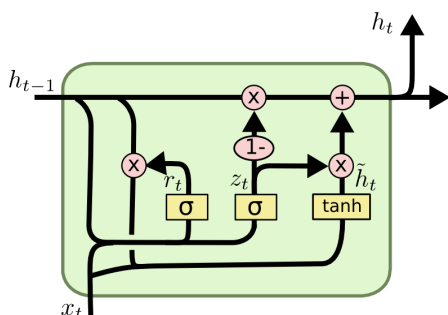
2

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.



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

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.



$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t])$$

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t])$$

$$\tilde{h}_t = \tanh(W \cdot [r_t * h_{t-1}, x_t])$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

6

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...

2

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 a255 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

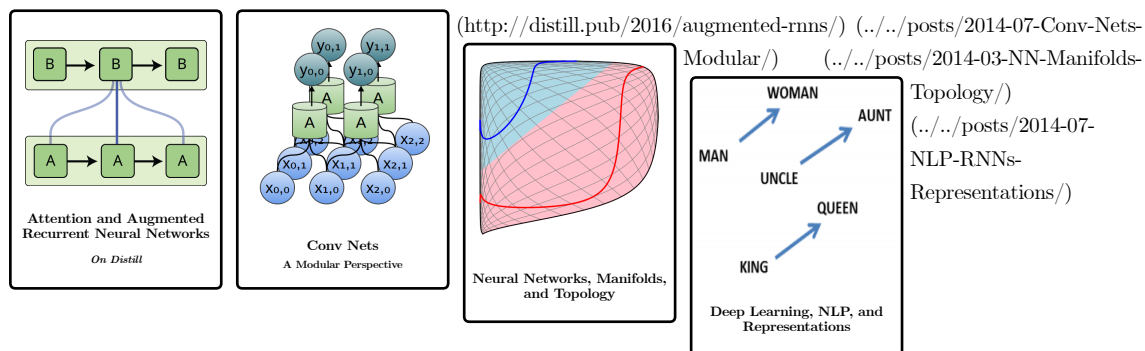
I'm grateful to a number of people for helping me better understand LSTMs, commenting on the visualizations, and providing feedback on this post.

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.

1. In addition to the original authors, a lot of people contributed to the modern LSTM. A non-comprehensive list is: Felix¹³ Gers, Fred Cummins, Santiago Fernandez, Justin Bayer, Daan Wierstra, Julian Togelius, Faustino Gomez, Matteo Gagliolo, and Alex Graves (<https://scholar.google.com/citations?user=DaFHynwAAAAAJ&hl=en>).↵

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OR SIGN UP WITH DISQUS [?](#)**Brandon Rohrer** • a year 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.

55 ^ | v • Reply • Share ›

**Dan Quang** • 2 years ago

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

23 ^ | v • Reply • Share ›

**chrisolah** Mod → **Dan Quang** • 2 years ago

I'm glad it helped!

2 ^ | v • Reply • Share ›

**Srinidhi Bheesette** → **chrisolah** • 6 months ago

Can these be used for particle pattern recognition?

^ | v • Reply • Share ›

**Dan Quang** → **chrisolah** • 2 years ago

I have to give a presentation soon to my department explaining LSTMs for my candidacy exam. Do you mind if I use some of these figures to explain LSTMs?

^ | v • Reply • Share ›

**chrisolah** Mod → **Dan Quang** • a year ago

Sorry I didn't respond earlier. For you, and anyone else reading, I'm happy for anyone to use these figures with attribution.

16 ^ | v • Reply • Share ›

**li kai** • 2 years ago

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

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

17 ^ | v • Reply • Share ›

**Daniel Bigham** → **li kai** • 2 years 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.

11 ^ | v • Reply • Share ›

**Alex Sosnovshchenko** • 2 years ago

I made Russian translation of this excellent post, I hope you will not mind.

<http://alexsosn.github.io/m...>

13 ^ | v • Reply • Share ›

**bobriakov** → **Alex Sosnovshchenko** • a year ago

Спасибо!

1 ^ | v • Reply • Share ›

**chrisolah** Mod → **Alex Sosnovshchenko** • a year ago

**chrisolah** MOD → Alex Sosnovsniuk • 2 years ago

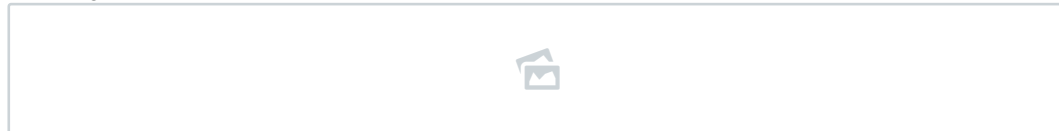
That looks lovely, Alex! Thanks for the translation!

1 ^ | ▾ • Reply • Share ›

**Steven Tang** • 2 years agoGreat 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 dimensionality 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!



4 ^ | ▾ • Reply • Share ›

**Atcold** → Steven Tang • 2 years ago h_t , C_t and \tilde{C}_t share the same dimensionality.

The size of \tilde{C}_t comes directly from the 'height' of W_C matrix (check \tilde{C}_t definition, above). W_C 's 'width' is instead equal to $\text{size}(h_t) + \text{size}(x_t)$.

3 ^ | ▾ • Reply • Share ›

**Majid al-Dosari** → Atcold • 2 years 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.

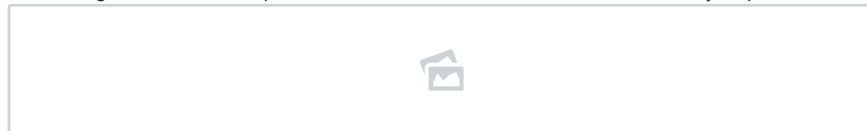
do you mean 'wide' matrix times 'tall' vector b/c you put h and x on top of each other?? that would equal a tall vector which can't be right. it can't be two vectors side by side b/c then the result would be a matrix.

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

^ | ▾ • Reply • Share ›

**chrisolah** Mod → Majid al-Dosari • a year ago

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



11 ^ | ▾ • Reply • Share ›

**hughperkins** → chrisolah • a year ago

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

12 ^ | ▾ • Reply • Share ›

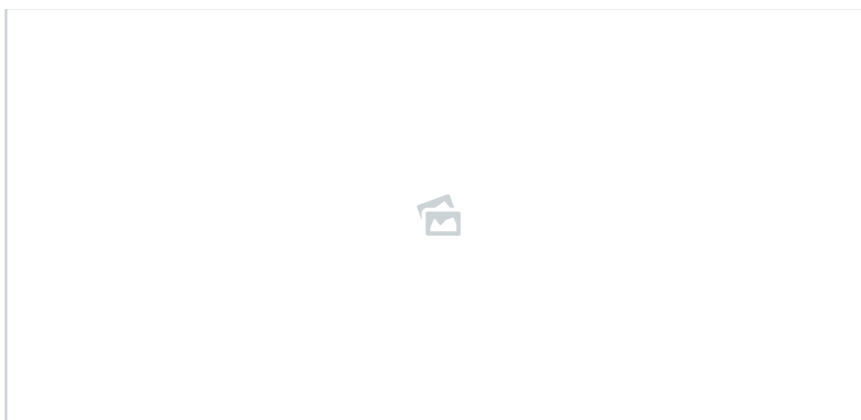
**Carl Thomé** → hughperkins • 8 months ago

Chris mentioned he did them in Inkscape. Beautiful stuff, indeed!

2 ^ | ▾ • Reply • Share ›

**Majid al-Dosari** → chrisolah • a year 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.



2 ^ | v • Reply • Share ›



chrisolah Mod → Majid al-Dosari • a year ago

Nice! :)

1 ^ | v • Reply • Share ›



Chris Anderson → chrisolah • 7 months ago

For that diagram, why is the input and hidden state split in two? I can see why the cell state is. Also, how/why do the yellow layers reduce the 4 inputs to 2 outputs?

^ | v • Reply • Share ›



chrisolah Mod → Chris Anderson • 7 months ago

The input and the hidden state come from different places. (See the original diagram, where they are two different lines that merge.)

The yellow layers have 2 outputs, because they need to output the same size as the cell state.

^ | v • Reply • Share ›



Chris Anderson → chrisolah • 7 months ago

Thanks for the reply.

Sorry, I meant why are they each split in two - why are there two inputs and two hidden states? How do you combine the 4 to produce 2?

^ | v • Reply • Share ›



Artsiom → chrisolah • 7 months ago

Hi Chris,

Could you please tell which software do you use to draw these histograms?

^ | v • Reply • Share ›



Ibrahim Sobh → Majid al-Dosari • a year ago

please have a look at:

<http://jmlr.org/proceedings...>

^ | v • Reply • Share ›



Majid al-Dosari → Majid al-Dosari • 2 years ago

oh i get it... two vectors on top of each other and height of W is size of vector.

^ | v • Reply • Share ›



Atcold → Majid al-Dosari • 2 years ago

Exactly. $Ax + By = [A|B][x/y]$, where $|$ concatenates horizontally and $/$ vertically.

4 ^ | v • Reply • Share ›

**Steven Tang** → Atcold • 2 years ago

Great, thanks for the explanation!

^ | v • Reply • Share ›

**Siljech** • a month ago

Great post! I'm trying to connect this knowledge with the practical use, using Tensorflow. In the simple RNN case where you have the tanh activation function, how does the input X_t look like if i have a translation model?

2 ^ | v • Reply • Share ›

**Steven Yin** • 2 years 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 ^ | v • Reply • Share ›

**Carl Thomé** → Steven Yin • 8 months ago

That's one of the most common applications for RNNs. Here's a good starting point in Keras:

<https://github.com/fchollet...>

^ | v • Reply • Share ›

**Zachary Jablons** • 2 years 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.

2 ^ | v • Reply • Share ›

**chrisolah** Mod → Zachary Jablons • 2 years ago

I've added the labels -- thanks for pointing that out!

1 ^ | v • Reply • Share ›

**Roman Lutai** • 5 months ago

Very informative and clear material you have made, author, thank you. But where can I find something like this with explaining of backpropagation for lstm? If it is even possible...

1 ^ | v • Reply • Share ›

**Aman Gill** • 6 months ago

Great Blog.

Can we not use batch normalization in vanilla RNNs to address the problem of Vanishing/Exploding gradients?

1 ^ | v • Reply • Share ›

**Halvord** • 6 months ago

This is great! What's missing, to me, is how the actual values of the various functions interrelate. That is, a chart with each number at each stage of the training sequence might help me understand how the negative feedback loops drive toward a finished result as training goes on.

1 ^ | v • Reply • Share ›

**Federico Ferreres** • 7 months ago

Thanks, it was very helpful to VISUALIZE the flow and rationale within a LSTM, and the best at such that I have seen. Adding some other architectures, and defining some visualization conventions prompts the idea of having a language to visualize math differently.

1 ^ | v • Reply • Share ›

**chrisolah** Mod → Federico Ferreres • 7 months ago

Glad you liked it!

^ | v • Reply • Share ›

**Bryan Baek** • a year ago

Really nice explanation about the LSTM. I was confused a lot but I just got quite better understanding.
Thanks a lot!

1 ^ | v • Reply • Share ›

**Beheen Trimble** • a year ago

Thank you.

1 ^ | v • Reply • Share ›

**skywalkerytx** • a year 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 $[H_{t-1}, X_t] = [[1,2,5],[3,4,6]]$?

1 ^ | v • Reply • Share ›

**Weijie Huang** • a year ago

In fact, how to calculate the " $Wf[H_{t-1}, X_t]$ "? Is it the same as $(Wf1 \cdot H_{t-1} + Wf2 \cdot X_t)$?

1 ^ | v • Reply • Share ›

**gaurav gupta** → Weijie Huang • 9 months 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 $Wf[h_{t-1}/x_t] \implies [M \times N][N \times 1]$ gives $[M \times 1]$. this the dimension of C_t .

^ | v • Reply • Share ›

**Ibrahim Sobh** → Weijie Huang • a year ago

I have the same question, do you have an answer?

please have a look at:

<http://jmlr.org/proceedings...>

^ | v • Reply • Share ›

**Ghislain Gagne** • a year ago

Excellent post, it made me understand better the inner workings of LSTM networks. Are LSTM nets suitable for time series prediction?

thanks

1 ^ | v • Reply • Share ›

**Rafael Espericueta** → Ghislain Gagne • a year ago

That's what LSTMs are for.

^ | v • Reply • Share ›

**David Krueger** • 2 years ago

Anyone's thoughts on IRNNs?

<http://arxiv.org/pdf/1504.0...>

1 ^ | v • Reply • Share ›

**Anshul Mittal** → David Krueger • 2 years ago

Can you specify exactly what you wanna ask?

^ | v • Reply • Share ›

**Jerry** → Anshul Mittal • 2 years ago

anshul mittal greatest FAC of all time

^ | v • Reply • Share ›

**ศิริชัย หลอดศิลป์** • 2 days ago

ขอชื่นชมและขอบคุณคุณ colah มากๆ สำหรับบทความนี้ที่ช่วยให้ผมเข้าใจ LSTM ได้ดีขึ้น



ฉันดีใจที่เพื่อน ๆ ติดตามมา การติดตามข้อมูลของงาน และขอขอบคุณเพื่อน ๆ ที่ช่วยเหลืองานมาตลอด

^ | v • Reply • Share ›



Nahua Kang • 5 days ago

Thanks a lot for this post on LSTM! May I ask what software you are using to draw all your graphs? Thank you!

^ | v • Reply • Share ›

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Groups & Group Convolutions

1 comment • 8 months ago •

Ryan Gnasbasik — You point out something that I think is true for vector spaces as well. In general vector spaces inherit properties from the fields ...

Calculus on Computational Graphs: Backpropagation

1 comment • 2 years ago •

atomicthumbs — Dang it, I KNEW I shouldn't have chosen Business Math!

Visual Information Theory

3 comments • 2 years ago •

Josh Chen — Almost, but not quite: the code for "bird" is 111. 111110 is still uniquely decodable as "bird fish", but not using the scheme you suggest.

Distill

26 comments • 3 months ago •

Daniel Seita — Um ... I'm just wondering if there are any Distill entries that are in the pipeline, being reviewed and so forth. There's only been one ...

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