Lab CudaVision
Learning Vision Systems on Graphics Cards (MA-INF 4308)

Recurrent Neural Networks

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Motivation

Why RNNs?

- Lots of **sequential** or **time-dependent** data:
  - Speech and Audio
  - Video
  - Sensor data

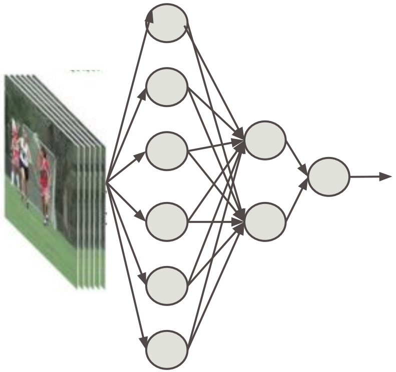
- ‘Snapshots’ are often not informative

⇨ Integrate temporal context into the network

Temporal Context

- How can we integrate temporal context in the network? 🤔

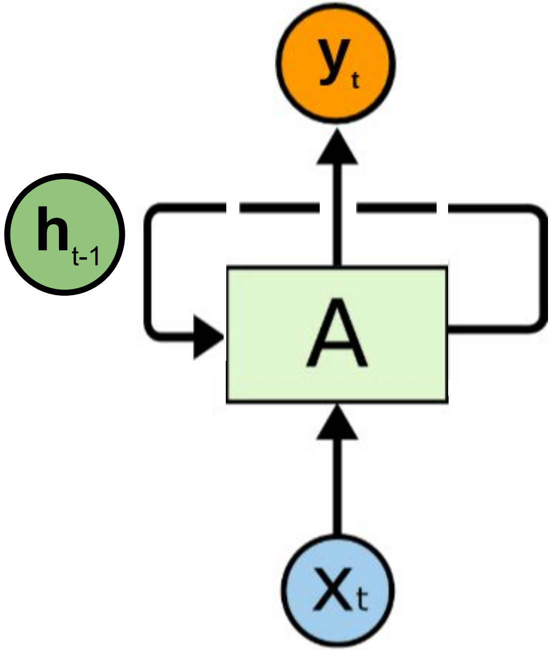
1. Feed whole sequence to a big network: **Bad Idea!:**
   - Too many parameters
   - No difference between spatial and time dimensions
   - Cannot handle real time



2. Model sequential behavior within the architecture
   - **Recurrent Neural Networks (RNNs)**

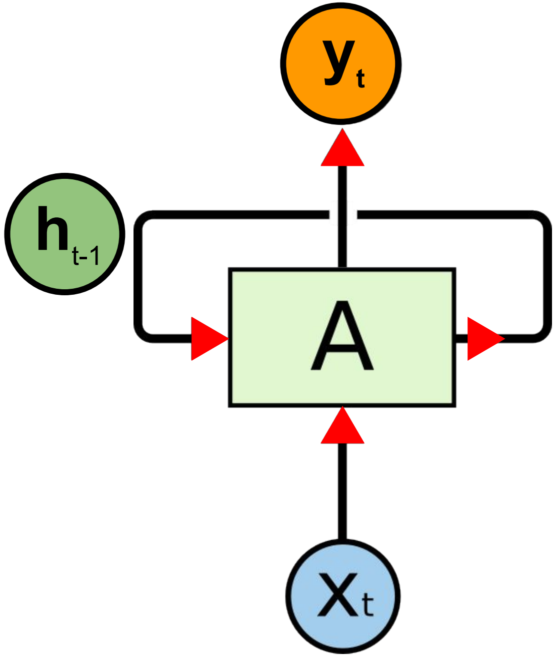
Simple RNNs

Simple RNNs



- RNNs include inner temporal loops
- Allow information to flow temporally
- Have been around since the 70s
  - For longer than CNNs!

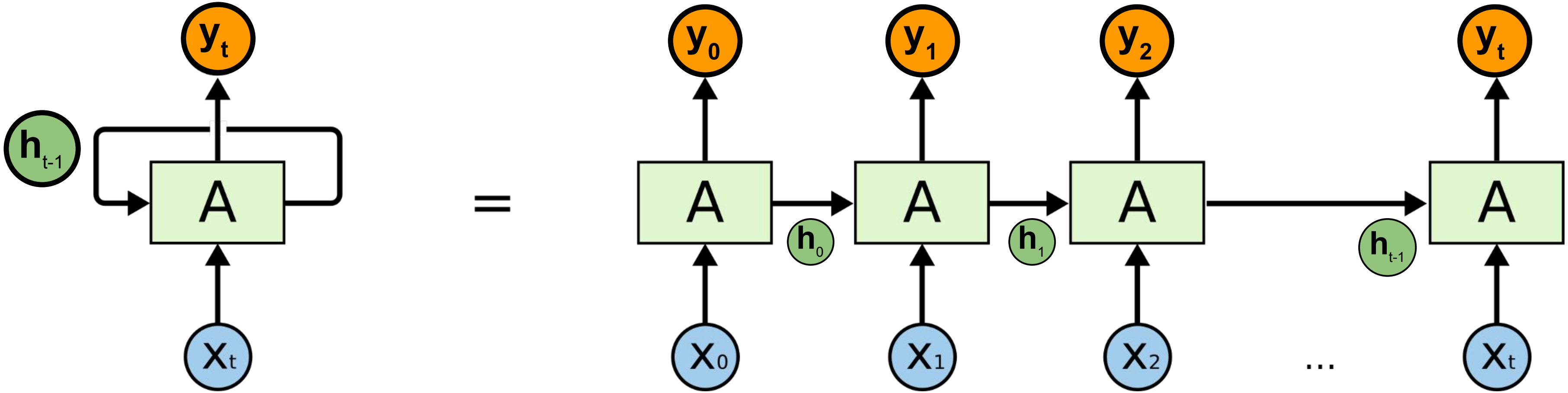
RNN Structure



- **Input** at time *t:* $\mathbf{X}_t$ is feed to a network
- **Extra input: Hidden state** $\mathbf{h}_{t-1}$ obtained by the unit
- **Outputs**
  - $\mathbf{Y}_t$: output with information from present and past
  - $\mathbf{h}_t$: next hidden state

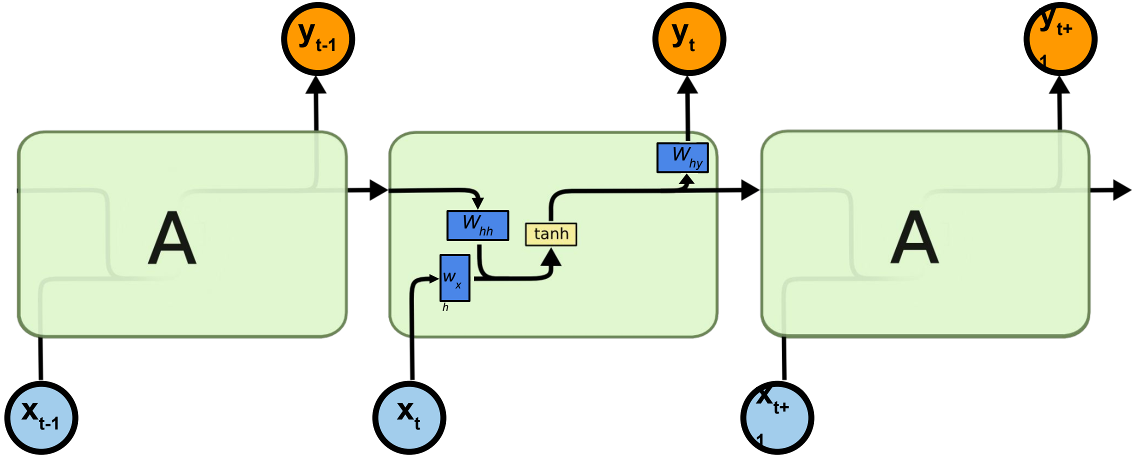
RNN Structure

- ‘Unfolded RNN’: sequence of copies of the **same** RNN cell
  - Temporal weight sharing
  - Each unit passes a hidden state as input to its successor



Vanilla RNN

$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t) \qquad y_t = W_{hy}h_t$$



Why not using the ReLU function?

Vanilla RNN

$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t) \qquad y_t = W_{hy}h_t$$

```
class RNN:
  # ...
  def step(self, x):
    # update the hidden state
    self.h = np.tanh(np.dot(self.W_hh, self.h) + np.dot(self.W_xh, x))
    # compute the output vector
    y = np.dot(self.W_hy, self.h)
    return y
```

Deep RNN

- We can stack several RNNs
  - Similar to CNNs
- Very common to use stack least two RNNs

Residual Stacked RNNs for Action Recognition

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Residual Stacking of RNNs for Neural Machine Translation

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Deep RNNs Encode Soft Hierarchical Syntax

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How to Construct Deep Recurrent Neural Networks

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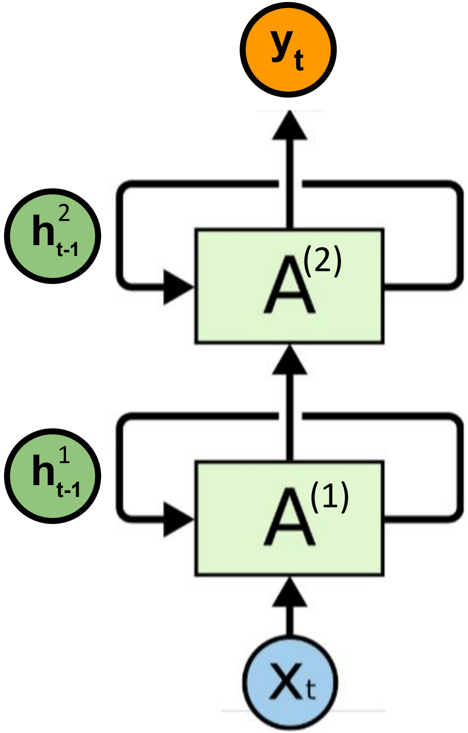
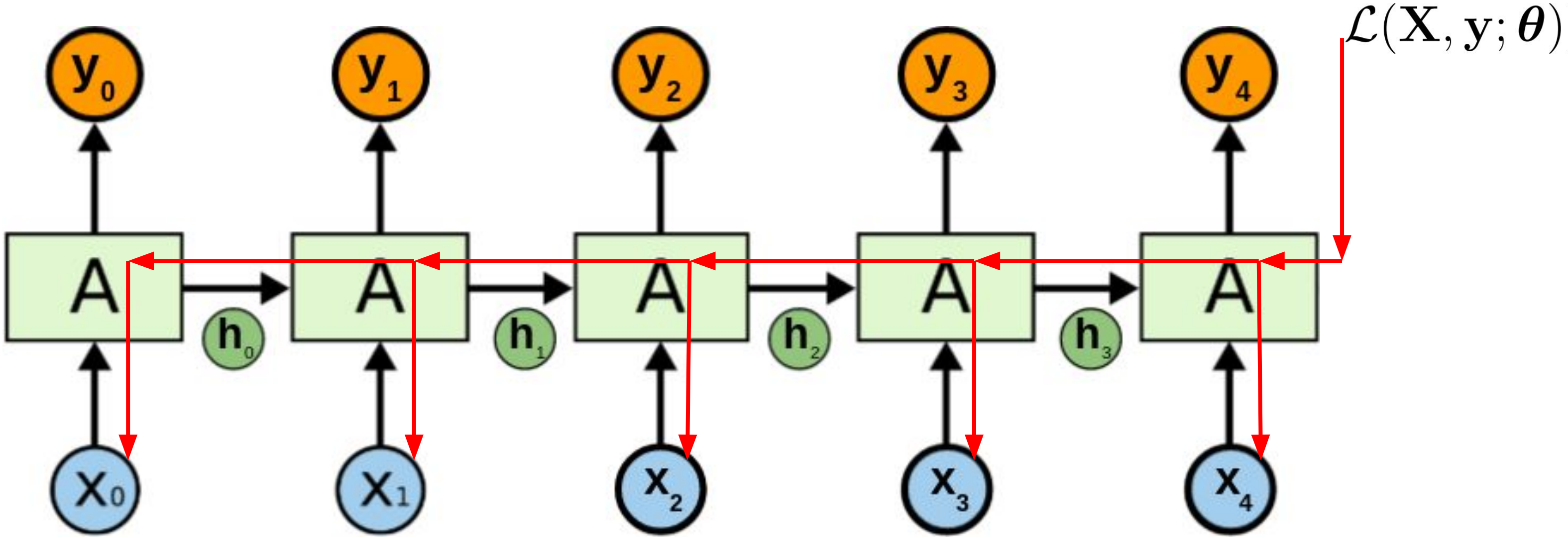


Problem with RNNs

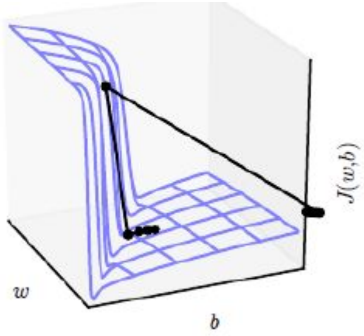
RNN Training

- RNNs are trained with backpropagation through time (BPTT)



Gradient Problem

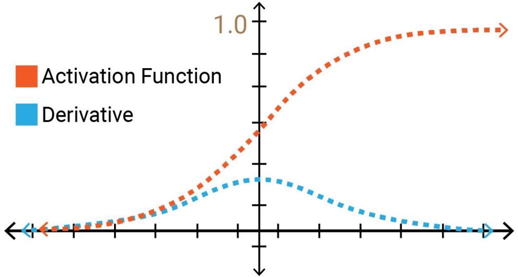
- Weights/Gradients are computed by a deep cascade of matrix multiplications and TanH nonlinearities



→ Gradients prone to vanishing or exploding

- **Exploding gradient:** just clip the gradients

- **Vanishing gradient:** hard to solve

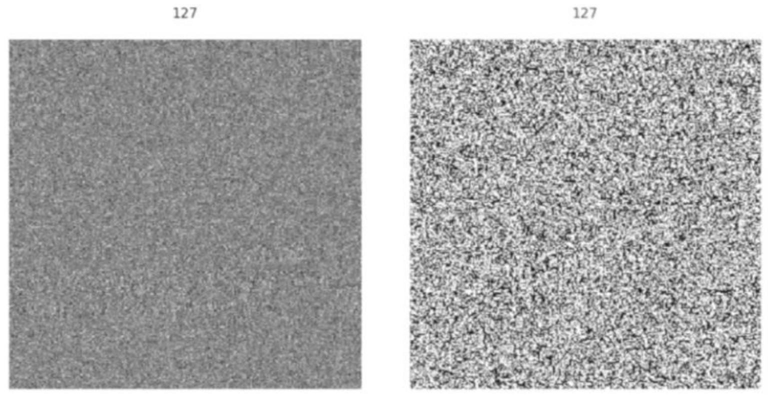


Memory Overwriting

- RNNs have it difficult to connect past and present for long time spans
- Hidden state is overwritten every time step

Q: Can we do better? 🤔

A: Yes!

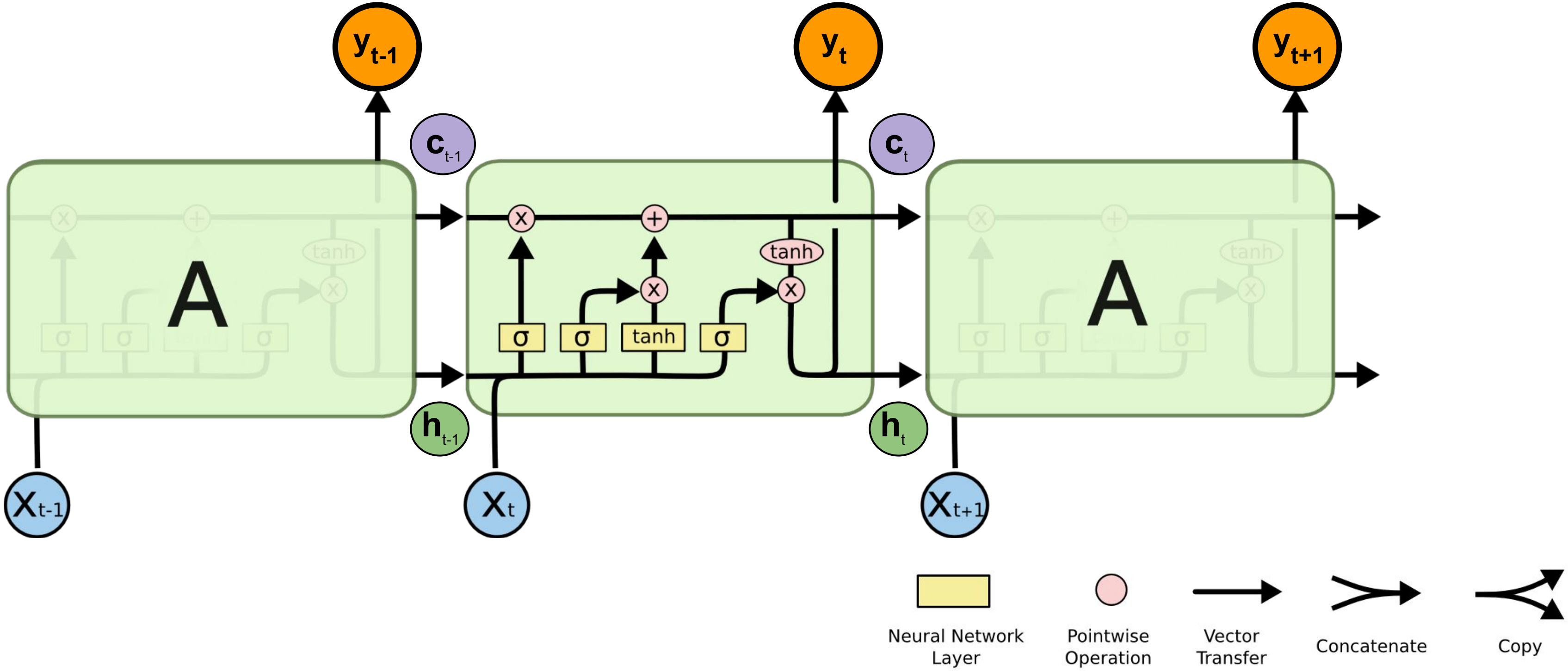


Long Short-Term Memory (LSTM)

Long Short-Term Memory

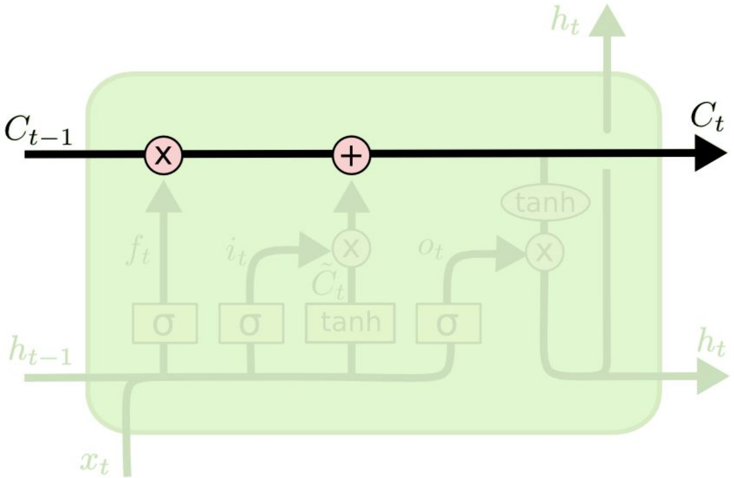
- Introduced by Hochreiter & Schmidhuber in 1997
- Designed to model long-term dependencies
- **Core idea:** using gates to control access and writing in an additional cell state

LSTM Structure



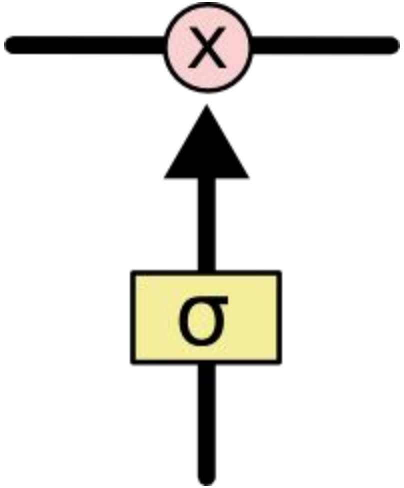
Cell State

- Runs across the entire LSTM with just some minor linear interaction
- LSTM modifies cell state using the so-called gates
- Cell state (*C*) ≠ Hidden state (*H*)



Gates

- **Gating** is a way of letting information through
- Gates are composed of a sigmoid activation and a pointwise product
- Sigmoid determines how much information goes through
  - **Zero:** Let nothing through
  - **One:** Let everything through

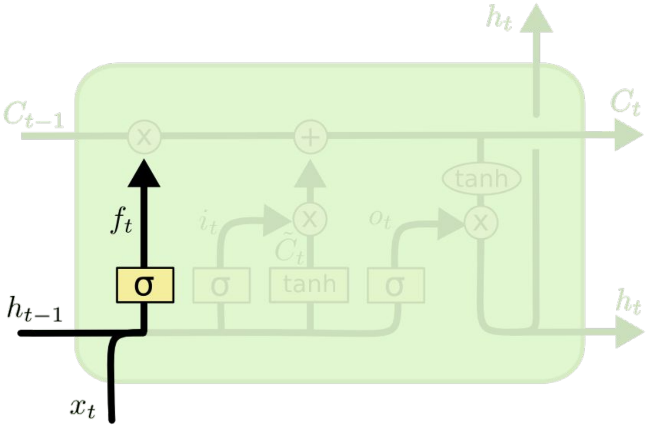


Step-by-Step LSTM Walk Through

Forget Gate

- Decides which information is removed from the cell state

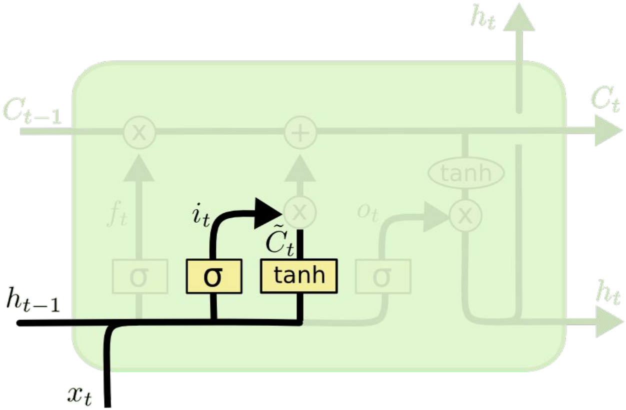
- Input and hidden state determine which values in cell state are forgotten



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

Input Gate

- Determines what new information goes into the cell state
- Two elements:
  - Sigmoid decides which values to update
  - TanH creates candidate values to update the cell state

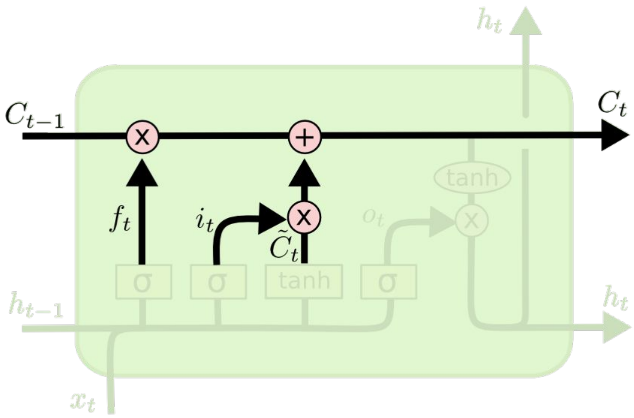


$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \ + \ b_i\right)$$
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \ + \ b_C)$$

Update Gate

- Updates the old cell state into the new cell state

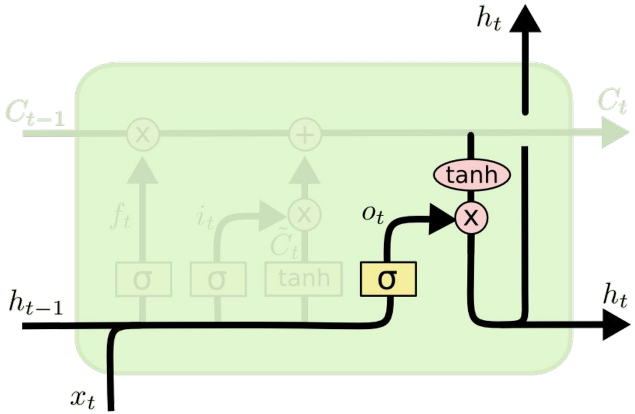
- Sequentially applies the results from the *forget* and *input* gates



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

Output

- Forms the output based on a filtered version of the input and states
- Input and hidden state select what information of cell state goes to the output

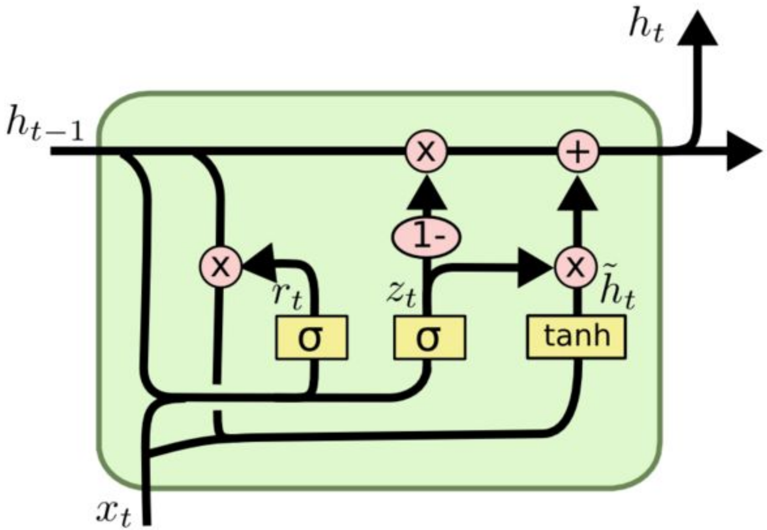


$$o_t = \sigma\left(W_o \left[h_{t-1}, x_t\right] + b_o\right)$$
$$h_t = o_t * \tanh\left(C_t\right)$$

LSTM Variants

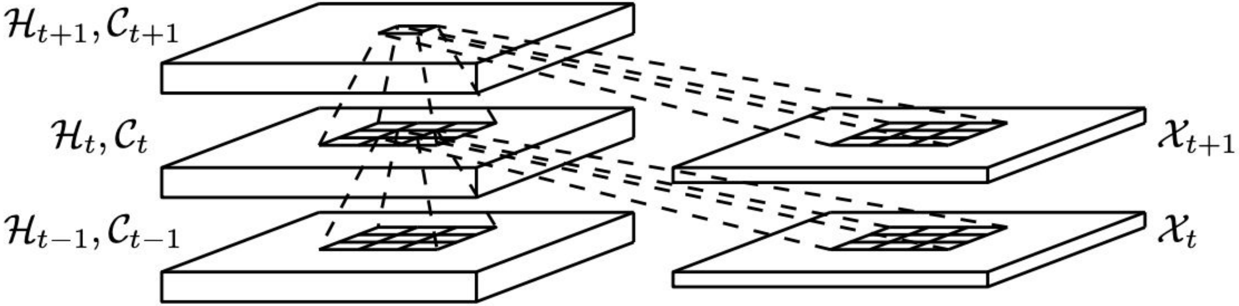
Gated Recurrent Unit

- Similar to LSTM, but 'simpler' and with fewer parameters
- Uses gates to control state
- Hidden and cell states are joined!



Conv-LSTM

- Spatio-temporal neural network
  - Combines ideas from Cnn's and RNNs
- Uses conv. structures in both the input and state transitions

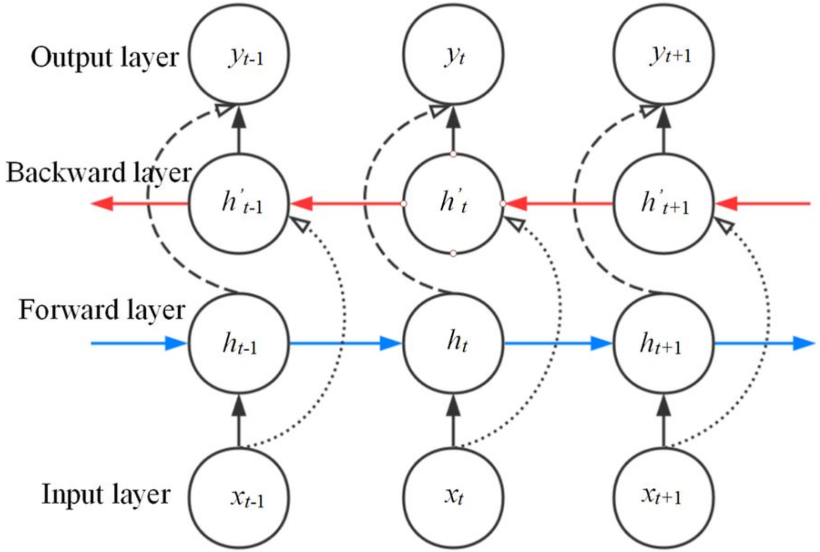


Bidirectional RNN

- Simultaneously look at past and future samples

- Uses two different states:
  - One in forward time direction
  - Other in backwards time direction

- Cannot handle real-time processing



Sequential Processing of Images

RNNs for Images

- RNNs can also be applied to datasets with fixed inputs, such as images
- **Idea:** Vectorize images and process them sequentially

Multiple Object Recognition with Visual Attention

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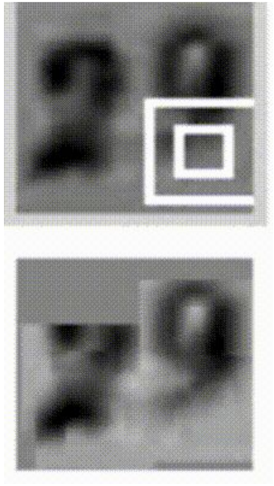
Abstract

We present an attention-based model for recognizing multiple objects in images. The proposed model is a deep recurrent neural network trained with reinforcement learning to attend to the most relevant regions of the input image. We show that the model learns to both localize and recognize multiple objects despite being given only class labels during training. We evaluate the model on the challenging task of transcribing house number sequences from Google Street View images and show that it is both more accurate than the state-of-the-art convolutional networks and uses fewer parameters and less computation.



RNNs for Images

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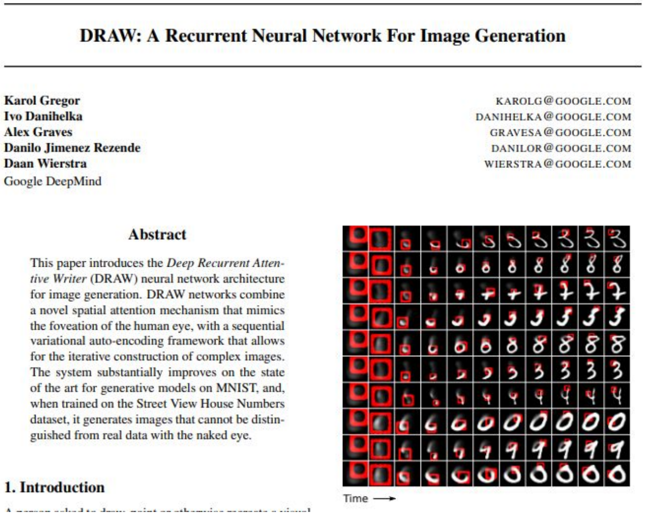
- **Idea:** Vectorize images and process them sequentially



DRAW: A Recurrent Neural Network For Image Generation

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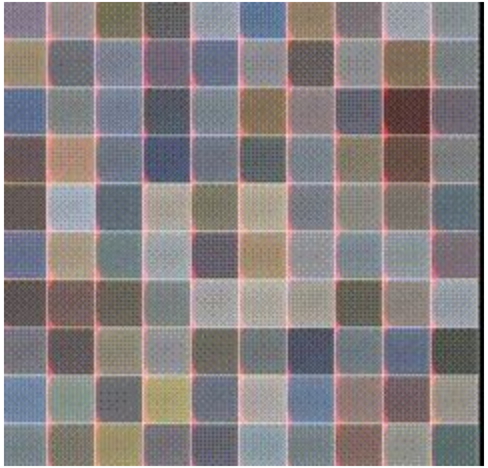
Abstract

This paper introduces the *Deep Recurrent Attentive Writer* (DRAW) neural network architecture for image generation. DRAW networks combine a novel spatial attention mechanism that mimics the foveation of the human eye, with a sequential variational auto-encoding framework that allows for the iterative construction of complex images. The system substantially improves on the state of the art for generative models on MNIST, and, when trained on the Street View House Numbers dataset, it generates images that cannot be distinguished from real data with the naked eye.

1. Introduction



RNNs for Images

- RNNs can also be applied to datasets with fixed inputs, such as images
- **Idea:** Vectorize images and process them sequentially

Pixel Recurrent Neural Networks

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Abstract

Modeling the distribution of natural images is a landmark problem in unsupervised learning. This task requires an image model that is at once expressive, tractable and scalable. We present a deep neural network that sequentially predicts the pixels in an image along the two spatial dimensions. Our method models the discrete probability of the raw pixel values and encodes the complete set of dependencies in the image. Architectural novelties include fast two-dimensional recurrent layers and an effective use of residual connections in deep recurrent networks. We achieve log-likelihood scores on natural images that are considerably better than the previous state of the art. Our main results also provide benchmarks on the diverse ImageNet dataset. Samples generated from the model appear crisp, varied and globally coherent.

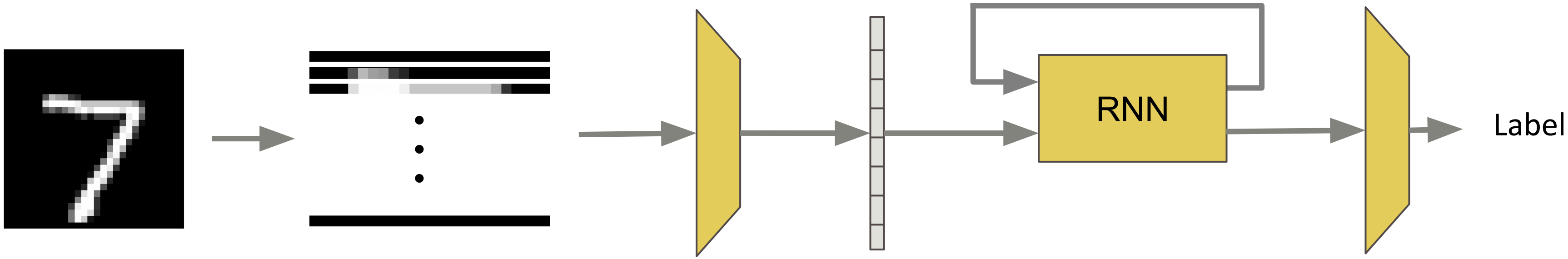
Figure 1. Image completions sampled from a PixelRNN.

eling is building complex and expressive models that are also tractable and scalable. This trade-off has resulted in a large variety of generative models, each having their advantages. Most work focuses on stochastic latent variable models such as VAE's (Rezende et al., 2014; Kingma & Welling, 2013) that aim to extract meaningful representations, but often come with an intractable inference step that can hinder their performance.

One effective approach to *tractably* model a joint distribu-

MNIST Sequential Classifier

- How to classify images with an RNN?
  1. Split images row-wise into a sequence of 28 28-dim vectors
  2. Embed 28-dim input into vector representation
  3. Sequentially feed embeddings to RNN
  4. Classify RNN output with a fully-connected layer



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