Deep Learning From Scratch

# Recurrent Neural Networks

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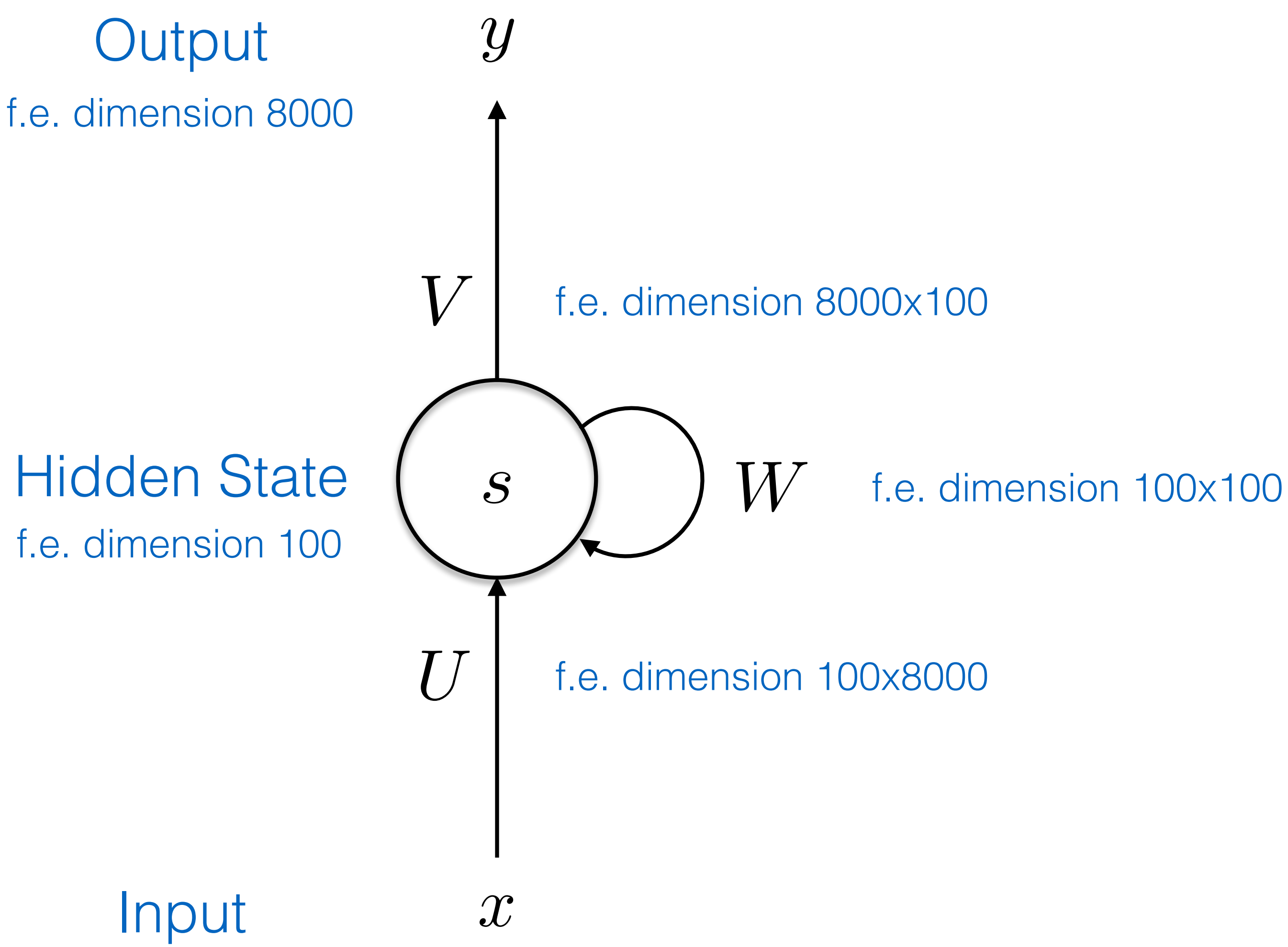
Classical neural networks, including convolutional ones, suffer from two severe limitations:

- They only accept a fixed-sized vector as input and produce a fixed-sized vector as output.
- They do not consider the sequential nature of some data (language, video frames, time series, etc.)

**Recurrent neural networks** overcome these limitations by allowing to operate over sequences of vectors (in the input, in the output, or both).

# Vanilla Recurrent Neural Network




TOTAL: 1,610,000 parameters

# Unrolling in time of a RNN

By unrolling we mean that we write out the network for the complete sequence.

Basic equations of the RNN

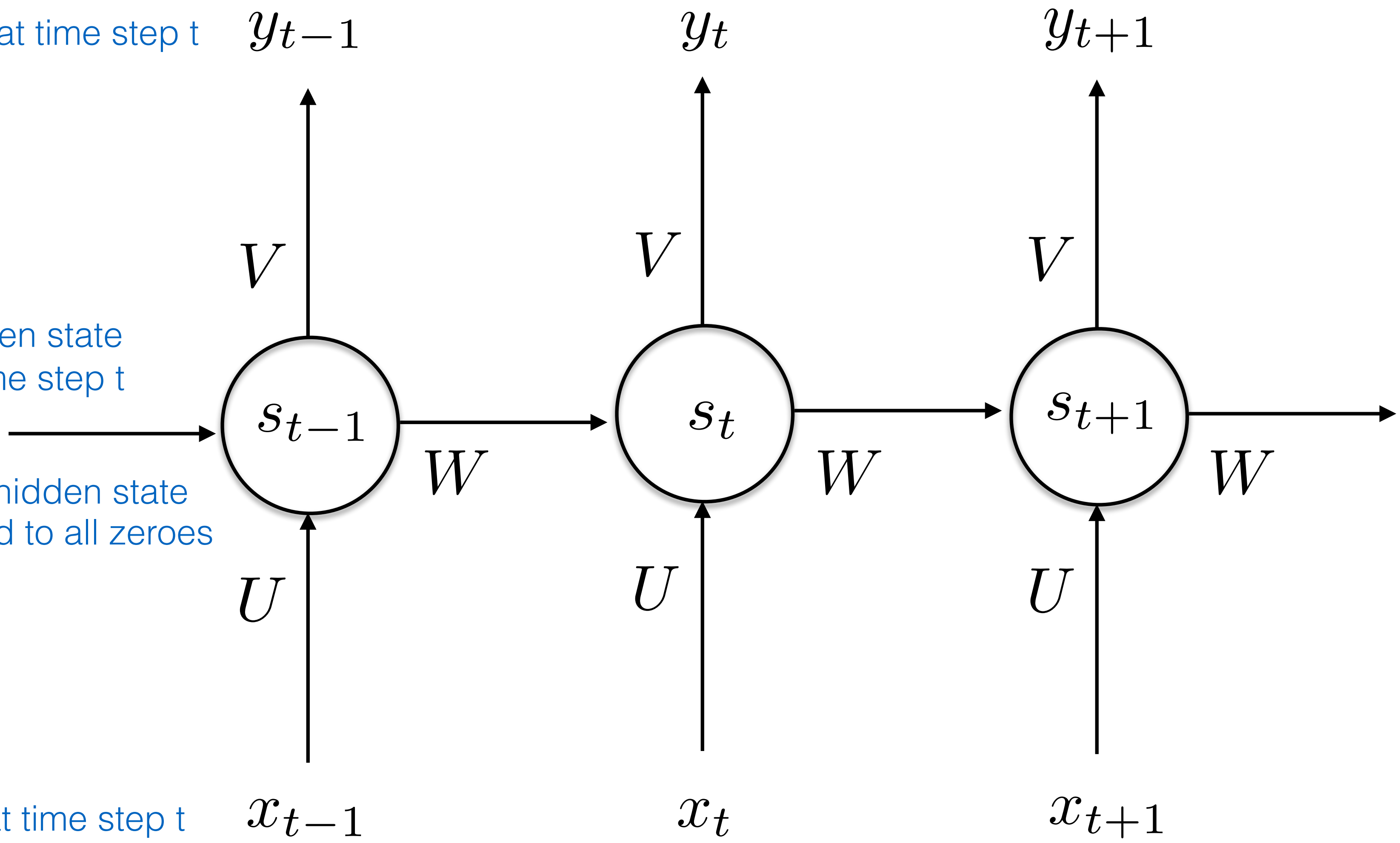
$$s_t = \tanh(Ux_t + Ws_{t-1})$$
$$y_t = \text{softmax}(Vs_t)$$

Output at time step t

Hidden state at time step t

The first hidden state is initialized to all zeroes

Input at time step t

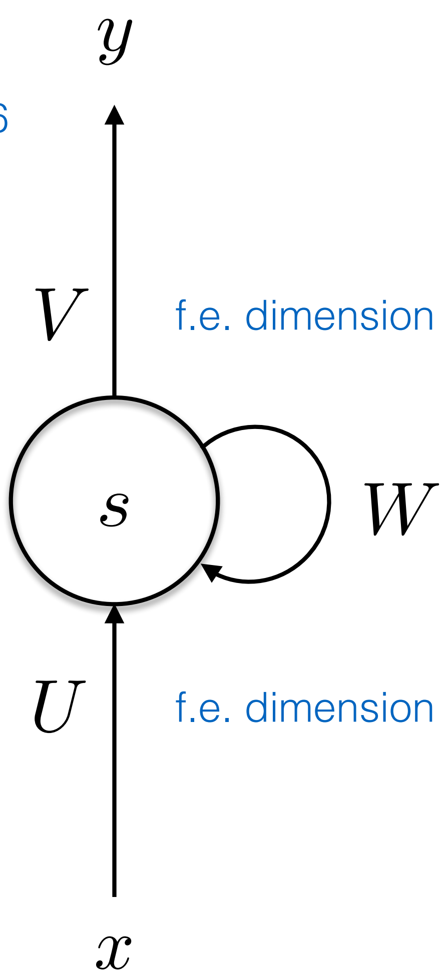


# Vanilla Recurrent Neural Network

minibatch version

Output

f.e. dimension 8000x256




f.e. dimension 8000x100

Hidden State

f.e. dimension 100x256

f.e. dimension 100x100

f.e. dimension 100x8000

Input

f.e. dimension 8000x256

Data: 4.121.600 floats = 16MB

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$s_t$

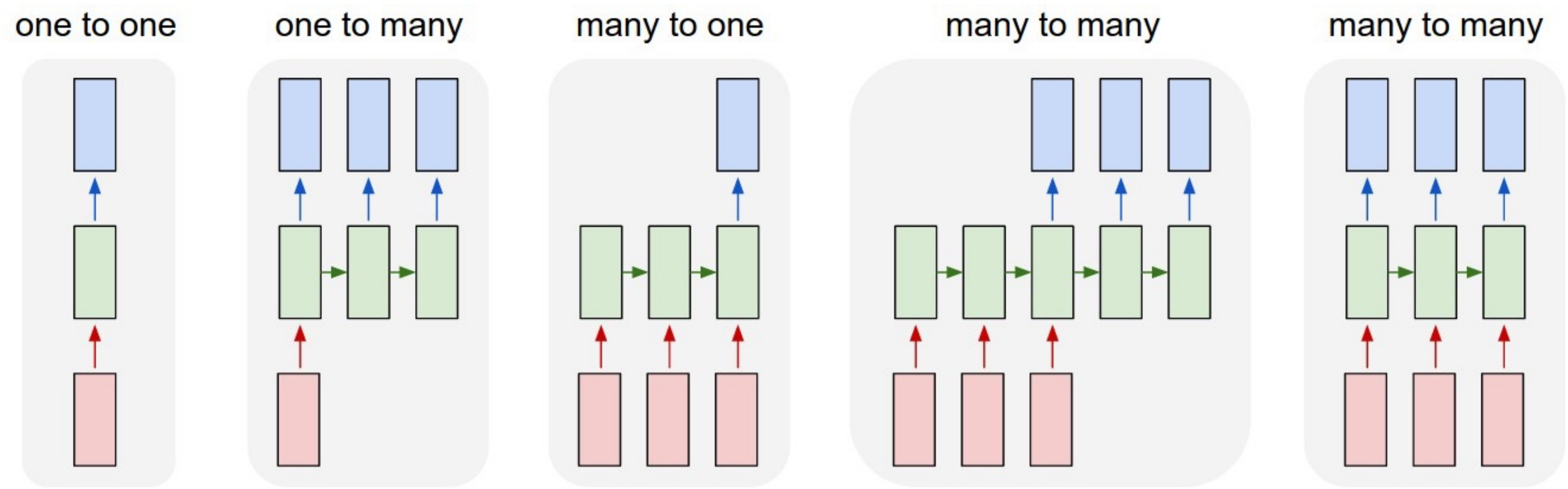
- We can think of the **hidden state** as a memory of the network that captures information about the previous steps.

$U, V, W$

- The RNN **shares the parameters** across all time steps.

$y_t$

- It is not necessary to have **outputs** at each time step.




Source: http://karpathy.github.io/2015/05/21/rnn-effectiveness/

RNN have shown success in:

- Language modeling and generation.
- Machine Translation.
- Speech Recognition.
- Image Description.
- Question Answering.
- Etc.

# RNN Training

Training a RNN is similar to training a traditional NN, but some modifications.

The main reason is that parameters are shared by all time steps: in order to compute the gradient at t=4, we need to propagate 3 steps and sum up the gradients.

This is called **Backpropagation through time** (BPTT).

# RNN Computation

```
class RNN:
    # ...
    def step(self, x):
        self.h = np.tanh(np.dot(self.W_hh, self.h) + np.dot(self.W_xh, x))
        y = np.dot(self.W_hy, self.h)
        return y
    # ...
```

`self.h` is initialized with the zero vector.

`Matrices` are initialized with random numbers.

## We can go deep by stacking RNN:

```
y1 = rnn1.step(x)
y2 = rnn2.step(y1)
```

# RNN Models

Vanilla RNNs trained with SGD are unstable/difficult to learn. Bit various **tricks** make our life easier:

- Gating Units
- Gradient Clipping
- Steeper gates
- Better initialization

# Gated Units

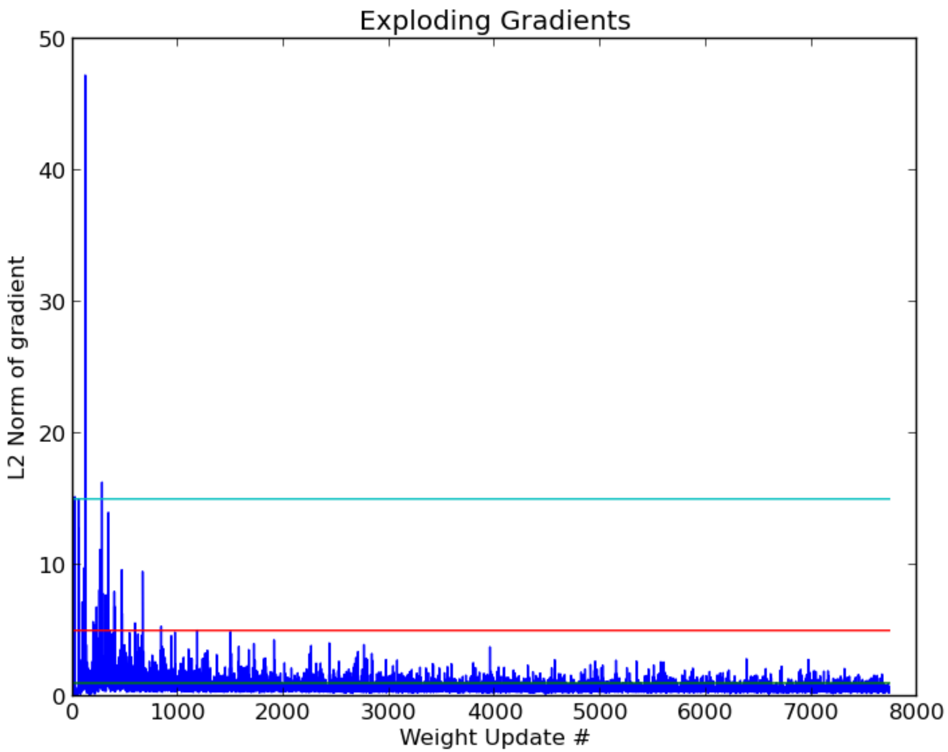
There are two types of gated RNNs:

• **Gated Recurrent Units** (GRU) recently introduced by K. Cho. GRU is simpler, faster, and optimizes quicker.

• **Long short term memory** (LSTM) by S. Hochreiter and J.Schmidhuber has been around since 1997 and has been used far more. LSTM may be better in the long run due to its greater complexity.

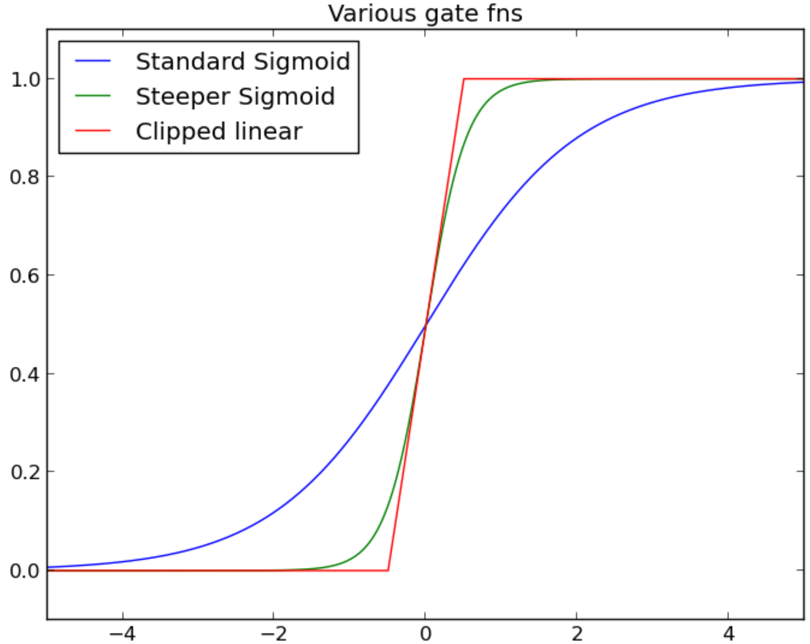
# Exploding gradients

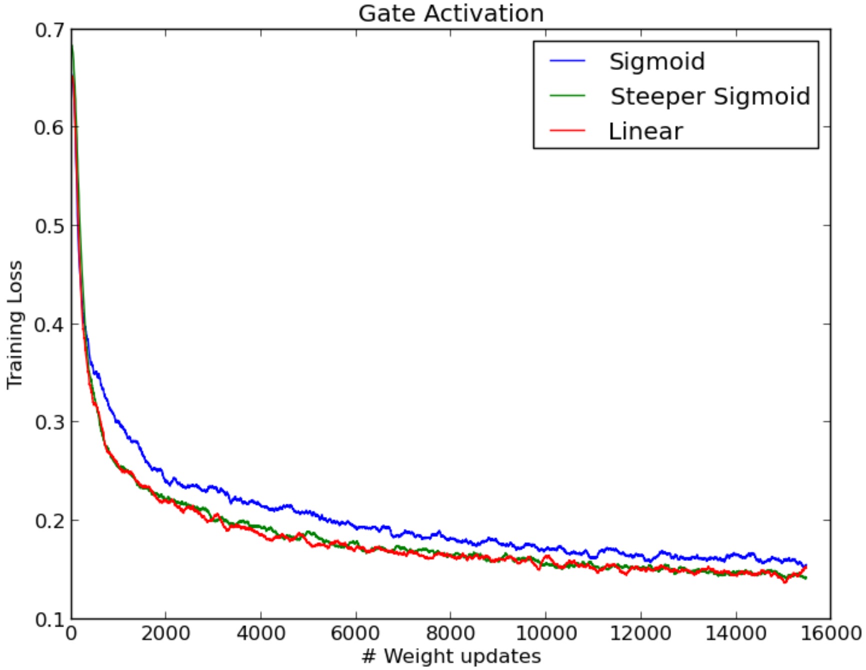
Exploding gradients may be a major problem for traditional RNNs trained with SGD. In 2012, R Pascanu and T. Mikolov proposed clipping the norm of the gradient to alleviate this.



# Steeper Gates

We can make the gates “steeper” so they change more rapidly from “off” to “on” so model learns to use them quicker.



# Better initialization

It has been showed that initializing weight matrices with random orthogonal matrices works better than random gaussian (or uniform) matrices.

# Gated Recurrent Unit (GRU)

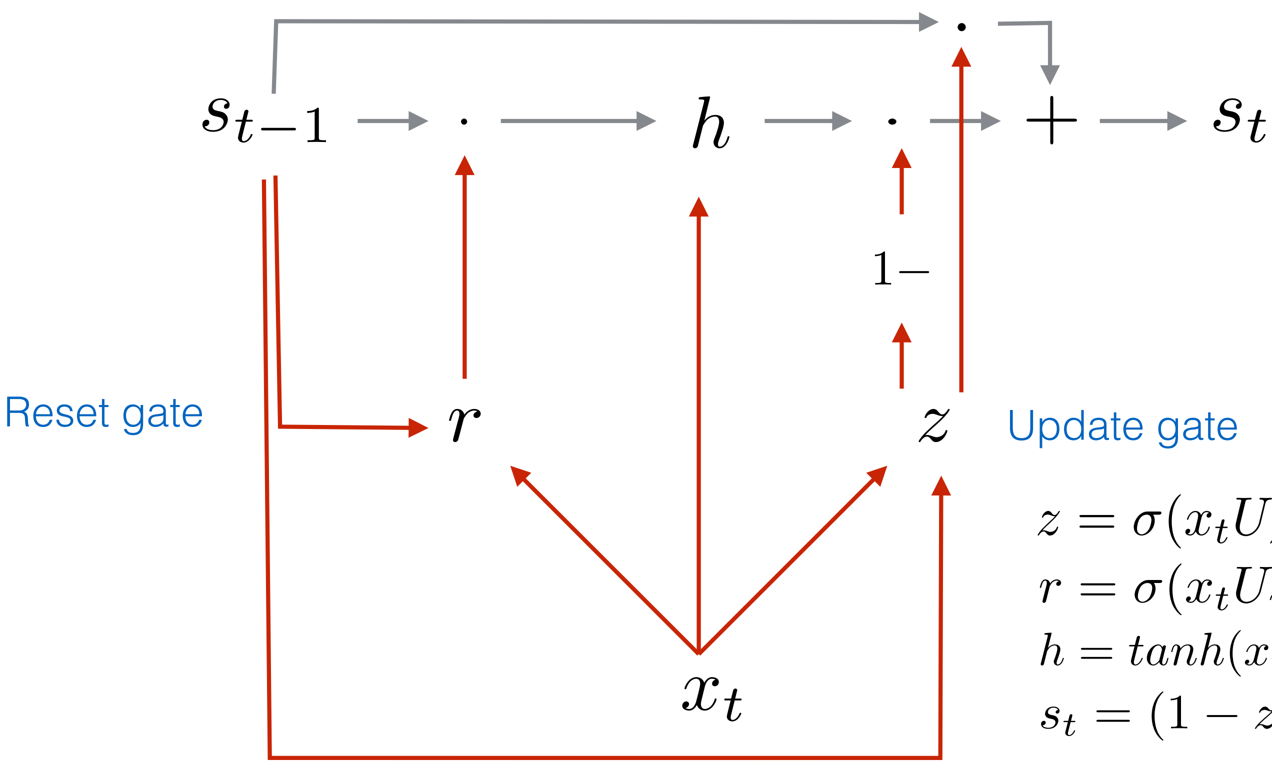
$$\begin{tikzcd} s_{t-1} \arrow[r] & + \arrow[r] & tanh \arrow[r] & s_t \\ & x_t \arrow[u] & & \end{tikzcd}$$

Modification of information flow and values

$$s_t = \tanh(Ux_t + Ws_{t-1})$$

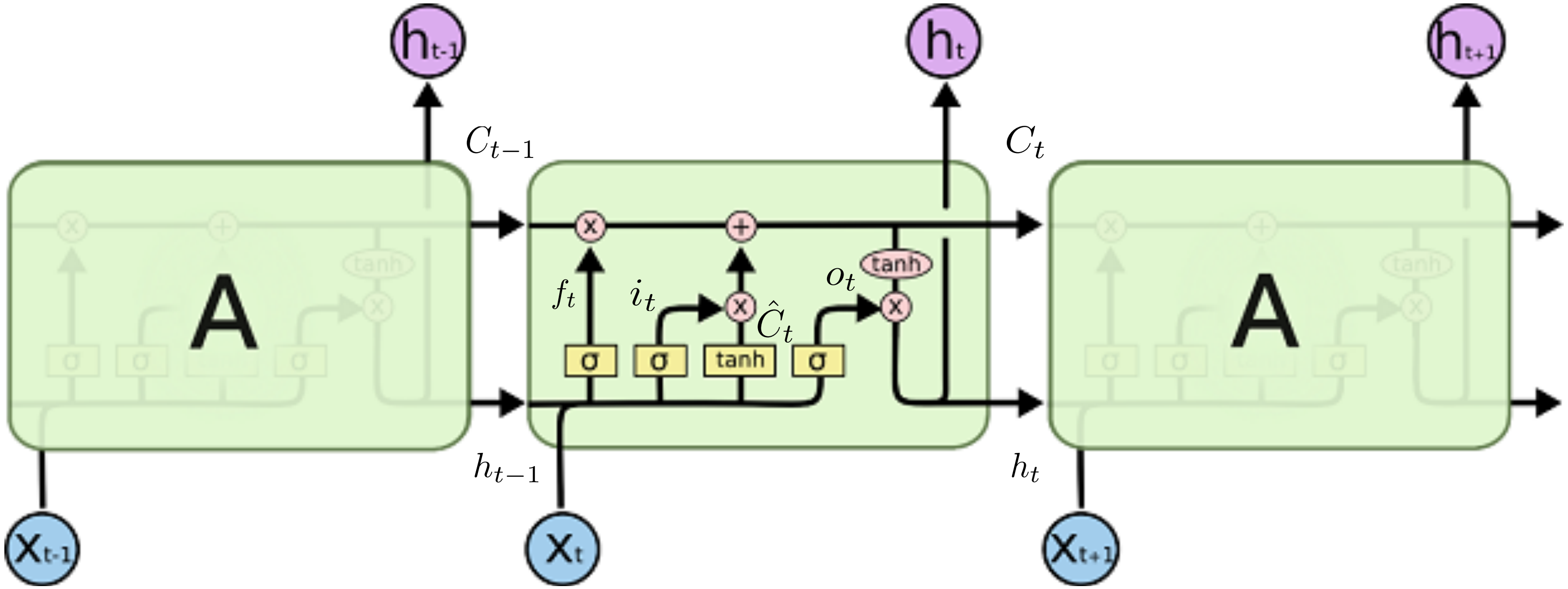
Vanilla RNN

GRU




$$z = \sigma(x_t U_z + s_{t-1} W_z)$$
$$r = \sigma(x_t U_r + s_{t-1} W_r)$$
$$h = tanh(x_t U_h + (s_{t-1} \cdot r) W_h)$$
$$s_t = (1 - z) \cdot h + z \cdot s_{t-1}$$

# Long Short Term Memory Unit (LSTM)




Source: http://colah.github.io/posts/2015-08-Understanding-LSTMs/

$$f_t = \sigma(W_f[h_{t-1} \cdot x_t] + b_f)$$
$$i_t = \sigma(W_i[h_{t-1} \cdot x_t] + b_i)$$
$$\hat{C}_t = \tanh(W_C[h_{t-1} \cdot x_t] + b_C)$$
$$C_t = f_t C_{t-1} + i_t \hat{C}_t$$
$$o_t = \sigma(W_o[h_{t-1} \cdot x_t] + b_o)$$
$$h_t = o_t \tanh(C_t)$$

# From text to RNN input

String Input

**The cat sat on the mat.**

Tokenize

| The | cat | sat | on | the | mat | . |
|---|---|---|---|---|---|---|

Indexing

| 0 | 1 | 2 | 3 | 0 | 4 | 5 |
|---|---|---|---|---|---|---|

Embedding

| 2.5 0.3 -1.2 | 0.2 -3.3 0.7 | -4.1 1.6 2.8 | 1.1 5.7 -0.2 | 2.5 0.3 -1.2 | 1.4 0.6 -3.9 | -3.8 1.5 0.1 |
|---|---|---|---|---|---|---|

# Example: Name Modeling

Let's build a sequential (Name) model with a Recurrent Neural Network. Let's say we have name of m chars.

A name model allows us to predict the probability of observing the name as:

$$P(c_1 \dots c_m) = \prod_{i=1}^{m} P(c_i | c_1 \dots c_{i-1})$$

Note that in the equation the probability of each char is conditioned on all previous chars.

# Example: Name Modeling

To train our model we need text to learn from a large dataset of names. Fortunately we don't need any labels to train a language model, just raw text.

I downloaded 52,700 Catalan names from a dataset available on


http://territori.gencat.cat/ca/01_departament/11_normativa_i_documentacio/03_documentacio/02_territori_i_mobilitat/cartografia/nomenclator_oficial_de_toponimia_de_catalunya/

# Example: Name Modeling

## Results

| |
|---|
| Alzinetes, torrent de les |
| Alzinetes, vall de les |
| **Alzinó, Mas d'** |
| Alzinosa, collada de l' |
| Alzinosa, font de l' |

| |
|---|
| Regueret, lo |
| Regueret, lo |
| **Regueró** |
| Reguerols, els |
| Reguerons, els |

| |
|---|
| Benavent, roc de |
| Benaviure, Cal |
| **Benca** |
| Bendiners, pla de |
| Benedi, roc del |

| |
|---|
| Vallverdú, Mas de |
| Vallverdú, serrat de |
| **Vallvicamanyà** |
| Vallvidrera |
| Vallvidrera, riera de |

| |
|---|
| Fiola, la |
| Fiola, puig de la |
| **Fiper, Granja del** |
| Firassa, Finca |
| Firell |

| |
|---|
| Terraubella, Corral de |
| Terraubes |
| **Terravanca** |
| Terrer Nou, Can |
| Terrer Roig, lo |