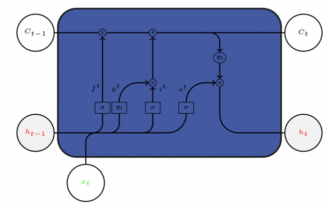

LSTM And GRU

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Sequence modeling

- Handle variable-length inputs
- Share parameters across the sequence
-

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Sequence modeling

- Handle variable-length inputs
- Share parameters across the sequence
- Keep track of long-term dependencies

Paul is a small boy and is hungry. He goes to the restaurant and eats a lot.

Sequence modeling

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Paul is a small boy and is hungry. He goes to the restaurant and eats a lot.

Solutions

- Activation function: using ReLU prevents σ' from shrinking the gradients when $x > 0$
- Weights and bias initialisation can help ($\boldsymbol{W} = \boldsymbol{I}, \boldsymbol{b}$=0)
- Think of another architecture

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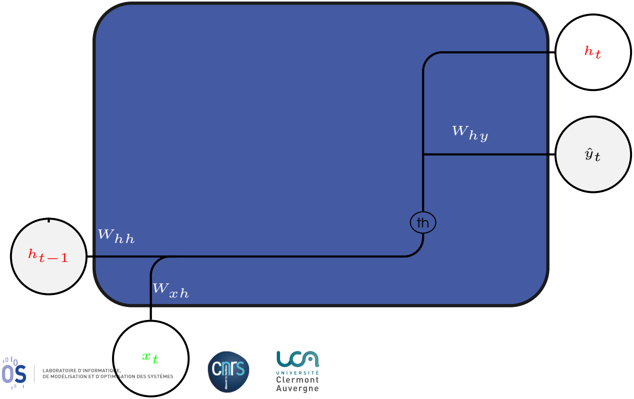
RECALL: RNN

1. Update hidden state

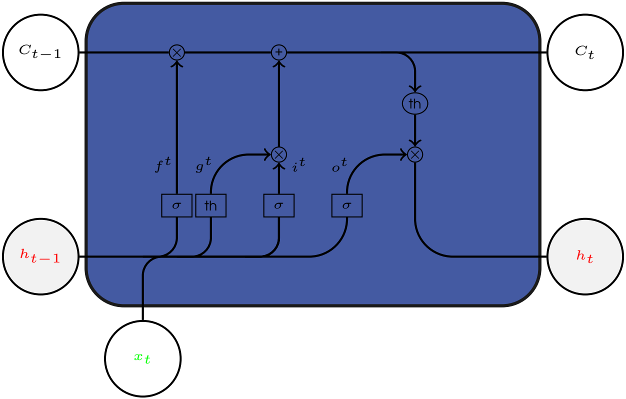
$$h_t = tanh(W_{xh}^T x_t + W_{hh}^T h_{t-1})$$

2. Compute output vector

$$\hat{y}_t = W_{hy}^T h_t$$



LSTM



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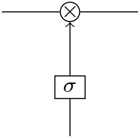
LSTM

Properties

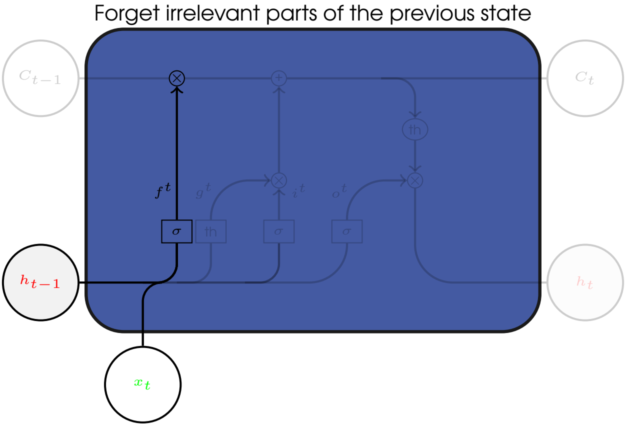
- Long Short Term Memory networks rely on gated cell to allow information tracking through time, even for several timesteps
- Contains computational blocks controling information flow
- Key concept: a persistent cell state C_t module, representation of past history
- in Keras: `tensorflow.keras.layers.LSTM(num_units)`

Gates

- Information is added or removed using gate structures.
- can let information through using eg. sigmoïd and pointwise multiplication



Inside LSTM: Forget gate



Inside LSTM: Forget gate

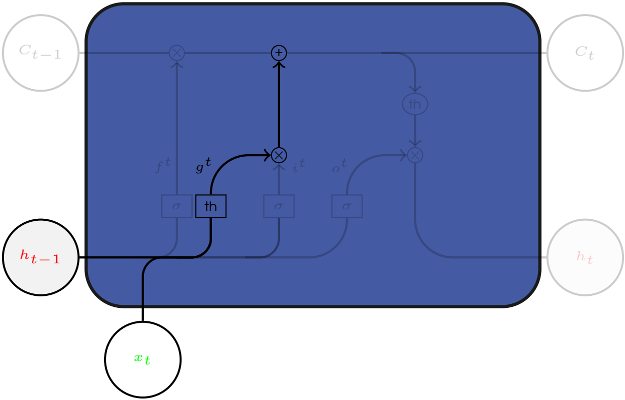
$$f^t = \sigma\left(\boldsymbol{W_f}^\top [\boldsymbol{x_t}, h_{t-1}] + b_f\right)$$

example: the state keeps the gender of the heroe in a text, for a good use of pronouns. If a new heroe appears, forget the gender.

- $f_t = 0$: completely forgetting previous state
- $f_t = 1$: completely keeping previous state
- b_f should be initilized with large values so that initially $f_t \approx 1$

Inside LSTM: Input neuron

Classic activation layer.



$$g^t = tanh\left(\boldsymbol{W_C}^\top [\boldsymbol{x_t}, h_{t-1}] + b_C\right)$$

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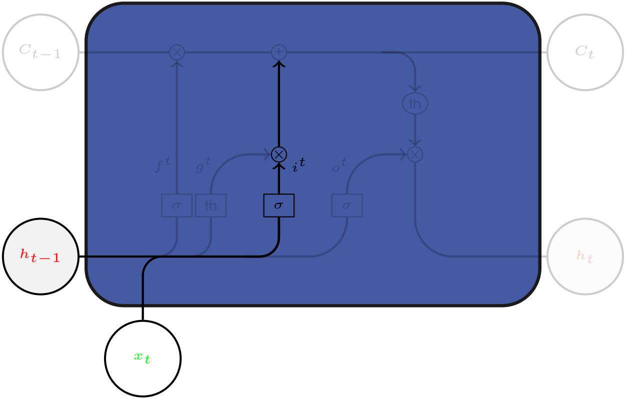
Inside LSTM: Update gate

Allows to weight the input neuron



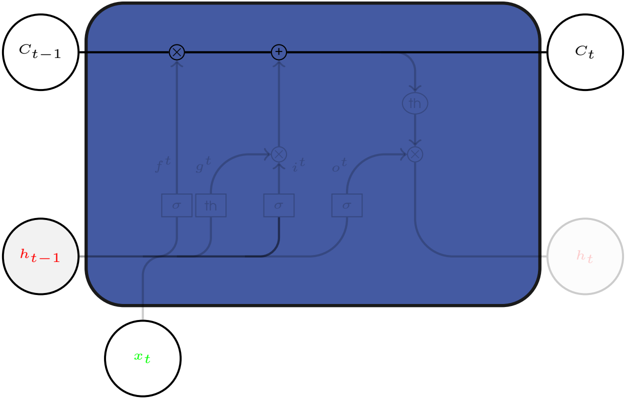
Inside LSTM: Update gate

$$i^t = \sigma\left(\boldsymbol{W_i}^\top [\boldsymbol{x_t}, h_{t-1}] + b_i\right)$$

- Decide the importance of the contribution of the input neuron at each timestep.
- g^t and i^t store relevant new information in the current state.

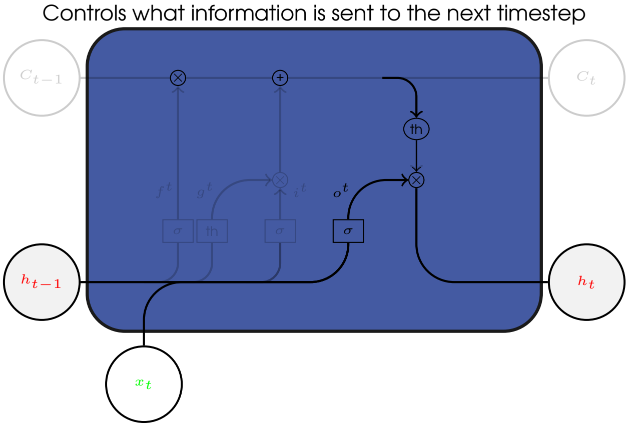
Inside LSTM: Update step

LSTM selectively update cell state values



$C_t = g^t.i^t + C_{t-1}.f^t$: assures that the derivatives of the loss w.r.t. C_t does not vanish.

Inside LSTM: Output gate



$$o^t = \sigma\left(\boldsymbol{W_o}^\top [\boldsymbol{x_t}, h_{t-1}] + b_o\right) \quad h_t = o^t tanh(C_t)$$

In summary:

$$
\begin{aligned}
f^t &= \sigma\left(\boldsymbol{W_f}^\top [\boldsymbol{x_t}, h_{t-1}] + b_f\right) \\
g^t &= tanh\left(\boldsymbol{W_C}^\top [\boldsymbol{x_t}, h_{t-1}] + b_C\right) \\
i^t &= \sigma\left(\boldsymbol{W_i}^\top [\boldsymbol{x_t}, h_{t-1}] + b_i\right) \\
C_t &= g^t.i^t + C_{t-1}.f^t \\
o^t &= \sigma\left(\boldsymbol{W_o}^\top [\boldsymbol{x_t}, h_{t-1}] + b_o\right) \\
h_t &= o^t tanh(C_t)
\end{aligned}
$$

Key concepts

Concepts

1. Maintain a separate state C_t from what is outputted
2. Use gates to control the information flow
   - can forget information (f^t)
   - can store relevant information from the x_t (g^t)
   - can selectively update state (i^t)
   - can return a filtered version of the state (o^t)
3. introduction of self-loops to produce paths where gradients can flow for long durations
4. Since the backward flow from C_t to C_{t-1} is direct, backpropagation through time is computed with uninterrupted gradient flow.

EXAMPLE

- Task: predicting the next word of a sentence based on previous ones.
- Hypothesis: the cell state C_t contains the gender of the subject

Paul is a clever guy. He has his own car. Cathy and Mary are their sisters.

1. First step (f^t): C_{t-1} contains the gender of the subject (Paul) to use proper pronouns (his). If a new subject arrive (Cathy and Mary), we may want to forget the old gender.
2. Second step: (g^t,i^t): what kind of information we want to store in C_t ? Here we may want to add the gender of the new subject (Cathy and Mary) to C_t
3. Third step (o^t): what we want to output. Since we see a new subject, we may want to output information relevant to verb (are)(eg. singular or plural subject)

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Variants

- LSTM with peephole connections
- Gates have access to C_{t-1}
- Bi-directional recurrent networks
- Gated Recurrent Units (GRU)
- Skip LSTMs
- ...

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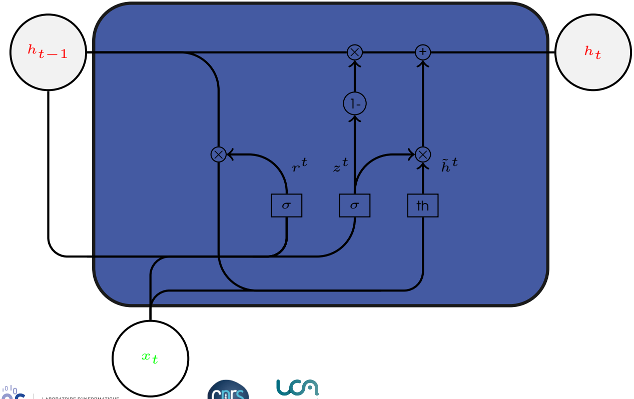
Gated Recurrent Units

Simplified version of LSTM:

- no o^t neither C_t
- only two gates
- easier to train



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Gated Recurrent Units

- reset gate r^t: determines how to combine $\boldsymbol{x_t}$ with h_{t-1}
- update gate z^t: what quantity of memory must be preserved (like a combination of f^t and g^t)

$$
\begin{aligned}
r^t &= \sigma\left(\boldsymbol{W_r}^\top [\boldsymbol{x_t}, h_{t-1}] + b_r\right) \\
z^t &= \sigma\left(\boldsymbol{W_z}^\top [\boldsymbol{x_t}, h_{t-1}] + b_z\right) \\
\tilde{h}^t &= tanh\left(\boldsymbol{W}^\top \left[\boldsymbol{x_t}, r^t h_{t-1}\right] + b_h\right) \\
h_t &= \left(1 - z^t\right) h_{t-1} + z^t \tilde{h}^t
\end{aligned}
$$

Gating network signals control how the present input and previous memory are used to update the current activation and produce the current state.

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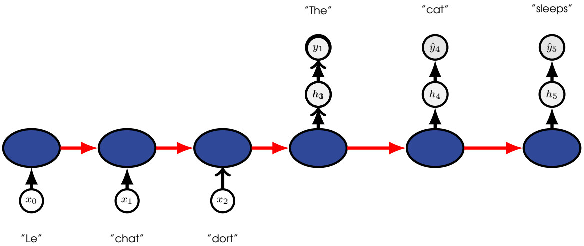
Machine translation

Many-to-Many architecture



- the sentence in the source language is a sequence
- it is transformed in a latent space by an LSTM encoder
- the sentence in the target language is a sequence
- it is captured by a LSTM decoder

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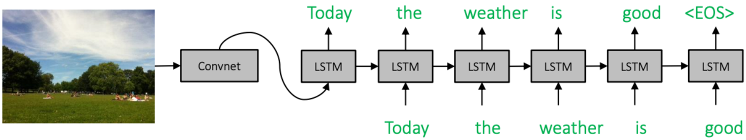
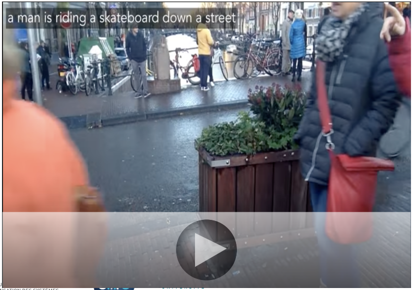
IMAGE CAPTIONING

Many-to-Many architecture





Timeseries modeling

Environmental modeling

KERAS

```
model = Sequential()
# 1 layer LSTM with batch size = 128
model.add(LSTM(128, input_shape=(...)))
model.add(Dense(..))
# Predicting the next word
model.add(Activation('softmax'))
model.compile(loss='binary_crossentropy',optimizer='adam', metrics=['accuracy'])
print(model.summary())


# Using embeddings
embedding_size = 32
model = Sequential()
model.add(Embedding(top_words, embedding_size, input_length=max_length))
model.add(LSTM(100))
model.add(Dense(1, activation='sigmoid'))
model.compile(loss='binary_crossentropy',optimizer='adam', metrics=['accuracy'])
print(model.summary())
```

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