RNN extensions, Memory Addressing and Attention

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Outline

Composing RNNs

Bidirectional RNNs

Motivation:

- Want to include future context

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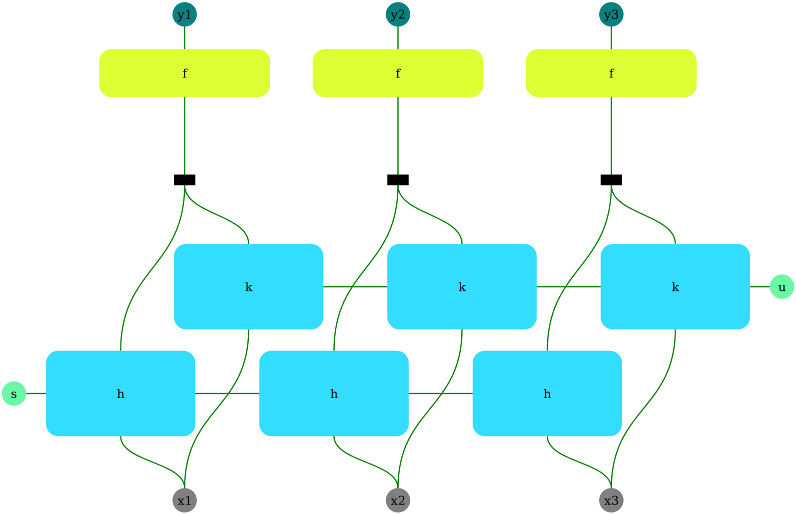
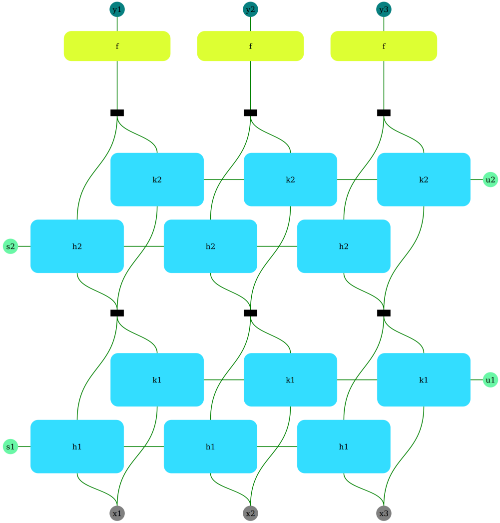
Assumes tight coupling between prediction at time t and input at time t.

- e.g. speech-to-text, text-to-speech

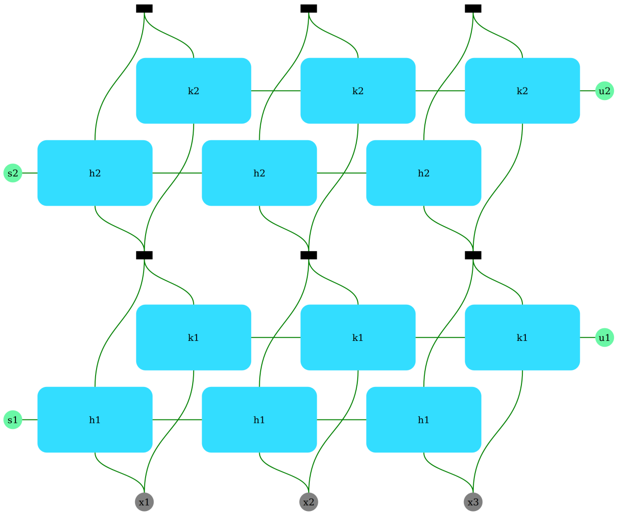
Bidirectional RNN - single layer



Bidirectional RNN - two layers



Bidirectional RNN - feature extraction



Encoder-decoder

For sequence-to-sequence problems with loose coupling between sequences

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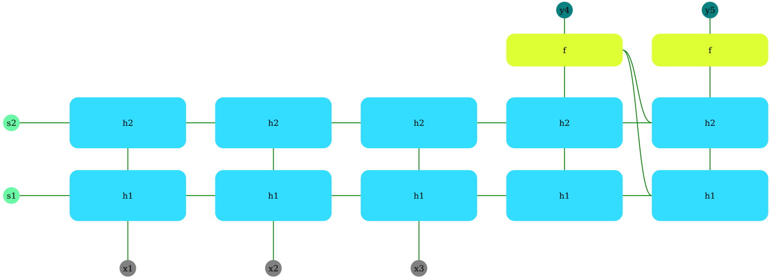
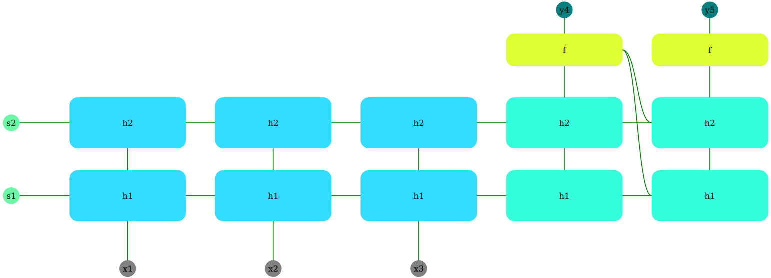
Example: sentence translation

1. Encode the "meaning" of sentence in source language into intermediate representation
2. Decode the "meaning" of the sentence into a representation in the target language

Encoder-decoder, shared RNN



Encoder-decoder, separate RNN



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Assume N source and N target languages.

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Newer models include attention

- Bidirectional RNN may then be used as *encoder*

Recursive neural networks

RNN Memory extensions

Addressing: location vs content-based

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$$p = \text{softmax}(\alpha)$$

$$v(q, M) = M_j \text{ with probability } p_j \qquad \text{hard addressing}$$

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Where does the query vector q come from?

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Perform query based on current state

$$q^t = Q^{(r)}(s^t)$$

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Get resulting vector r^t by

$$p^t = \text{softmax}(\alpha^t)$$

$$r^t = v(q^t, M^{t-1}) = \sum_{j=1}^{J} p_j^t M_j^{t-1}$$

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How to make update?

$$M_j^t = (1 - p_j^w) M_j^{t-1} + p_j^w w^t \qquad \text{overwrite}$$

$$M_j^t = M_j^{t-1} + p_j^w w^t \qquad \text{residual update}$$

Exists corresponding *hard* update rules

RNN example with external memory - how to use it

Update function:

$$s^t = h(x^t, s^{t-1}, y^{t-1}, r^{t-1})$$

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Could also add directly to output function

$$y^t = f(s^t, r^t)$$

External memory - multiple read/write *heads*

- E.g. define N query, key function pairs $(Q_1^{(r)}, K_1^{(r)}), \ldots,$ $(Q_N^{(r)}, K_N^{(r)})$
  - Concatenate all of the retrieved vectors, $r^t = (r_1^t, \ldots, r_n^t)$.

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- May use same matching function

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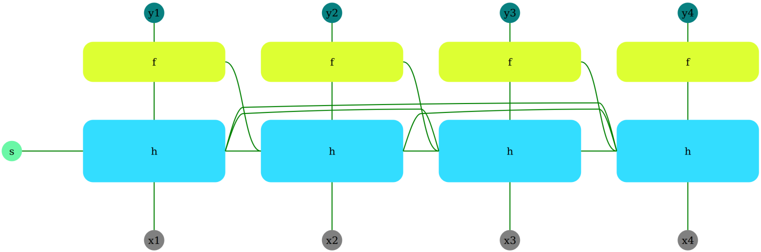

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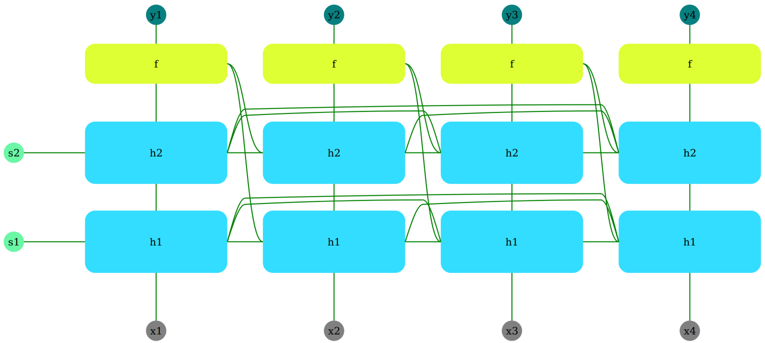
\end{aligned}$$

Then proceed with "previous state" $\tilde{s}^{t-1}$

$$s^t = h(x^t, \tilde{s}^{t-1}, y^{t-1})$$

Attending to previous states III



Attention

Image captioning with RNN and content-based attention

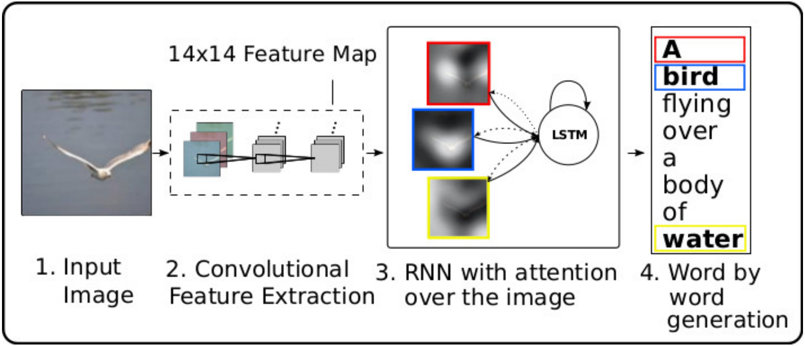


Figure: Illustration from "Xu, Kelvin, et al. "Show, attend and tell: Neural image caption generation with visual attention." International conference on machine learning. 2015."

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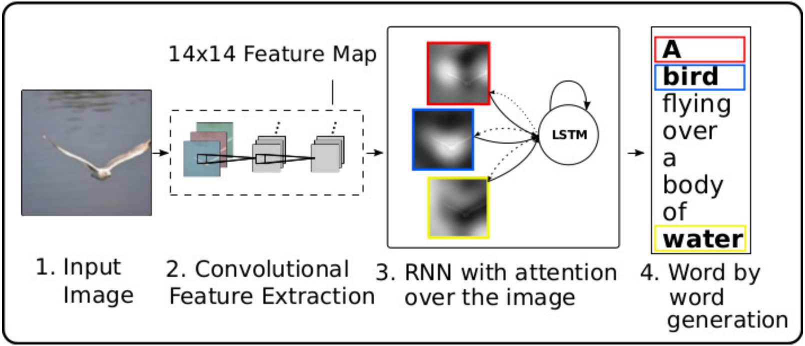

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- Content based addressing with 14×14 conv features as "memory"

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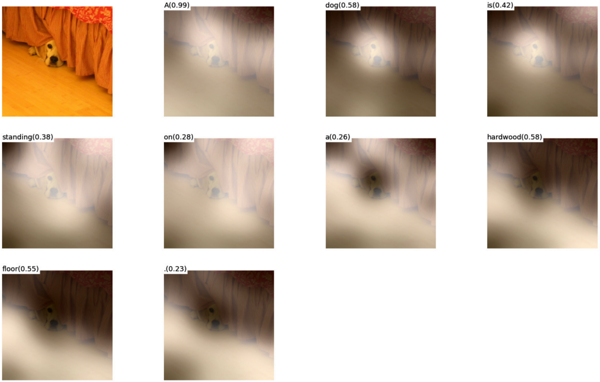

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Usually extract some lower resolution crops as well.

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