Deep Learning

15 Encoder-Decoder Models & Attention

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Jan-May 2023

Encoder-Decoder Model

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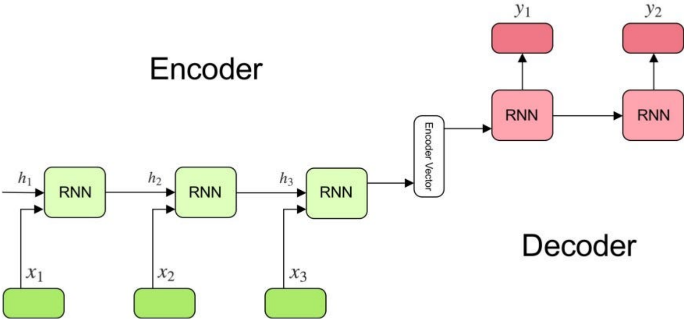
3. We have an RNN consuming the i/p sequence $(y_1^{t-1}) \rightarrow$ **Encoder**
4. We have another RNN predicting the o/p (sequence of words after the i/p) $\rightarrow$ **Decoder**

Encoder-Decoder Model

భారతీయ సాంకేతిక విజ్ఞాన సంస్థ హైదరాబాద్
भारतीय प्रौद्योगिकी संस्थान हैदराबाद
Indian Institute of Technology Hyderabad



Credits: Simeon Kostadinov

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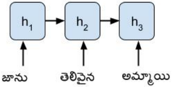
3. Basis for a lot of applications
4. Let's consider machine translation...

Encoder-Decoder for Machine Translation

Input sequence: $x_1, x_2, \ldots. x_T$

Output sequence: $y_1, y_2, \ldots. y_{T'}$

Encoder: $h_t = E(x_t, h_{t-1})$



Sequence to sequence learning by Sutskever et al. NeurIPS 2014

Encoder-Decoder for Machine Translation

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Last hidden state $h_T \rightarrow$ Initial state of the Decoder S_0 and the context information C
E.g. $S_0 \leftarrow h_T$ + dense layers, and $C \leftarrow h_T$

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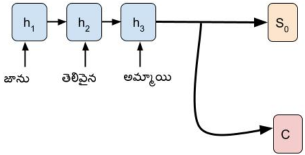

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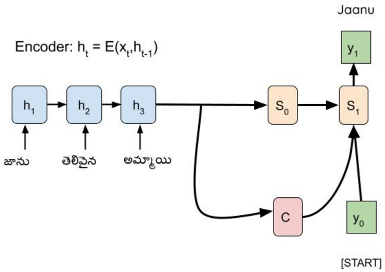

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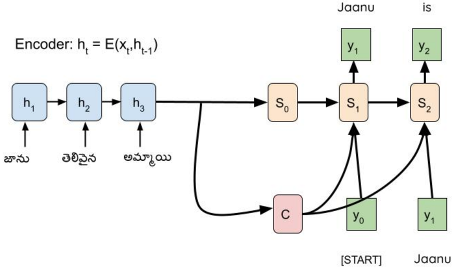

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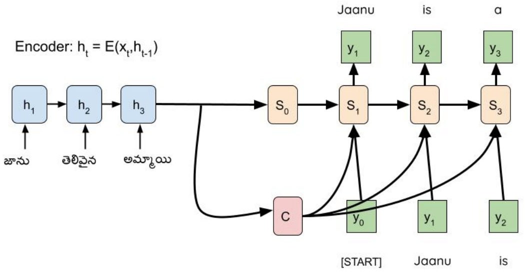

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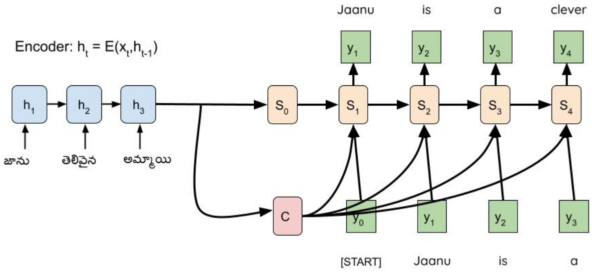

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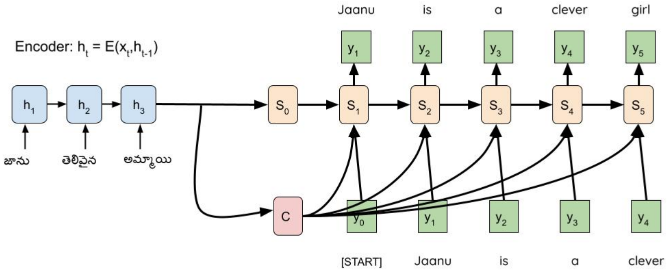

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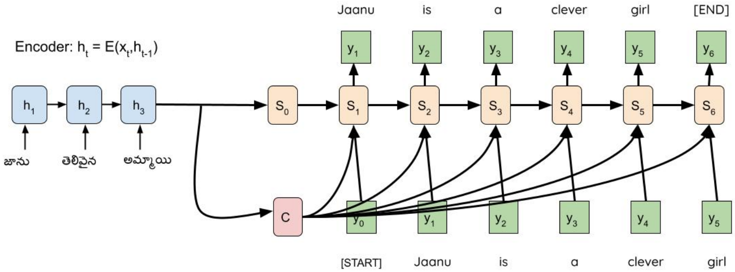

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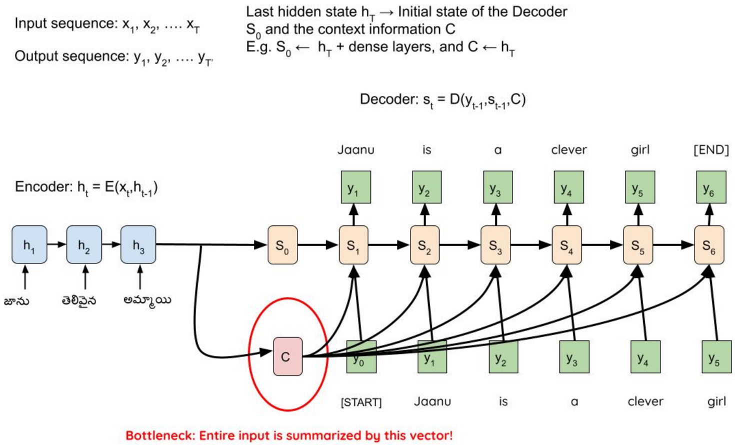

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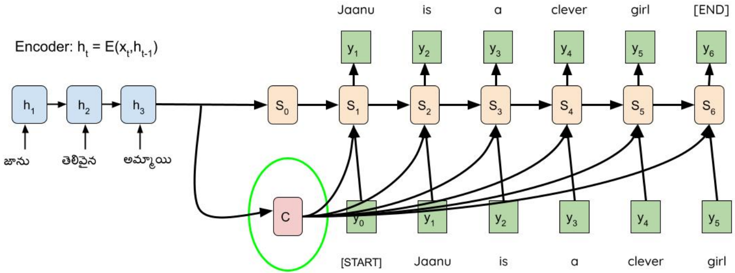

Solution: use different context at each time step!

Sequence to sequence learning by Sutskever et al. NeurIPS 2014

Encoder-Decoder for Machine Translation with Attention

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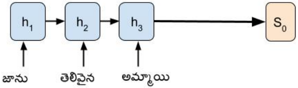
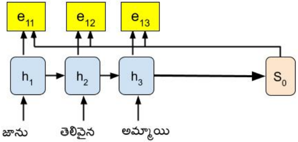


Encoder-Decoder for Machine Translation with Attention

Compute the alignment scores

$e_{t,i} = f_{att}(s_{t-1}, h_i)$ f_{att} - couple of dense layers



Neural Machine Translation with aligning by Bahdanau et al. ICLR 2015

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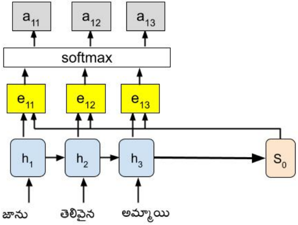

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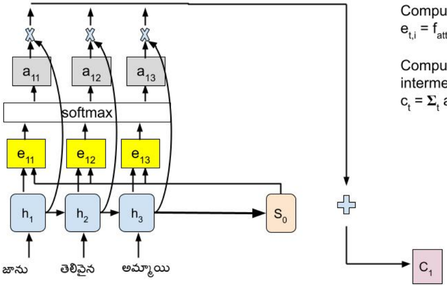

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$c_t = \Sigma_t \, a_{i,t} \cdot h_t$

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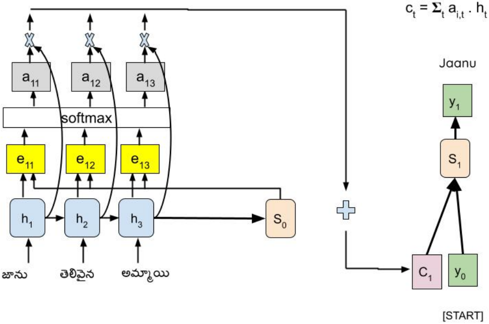

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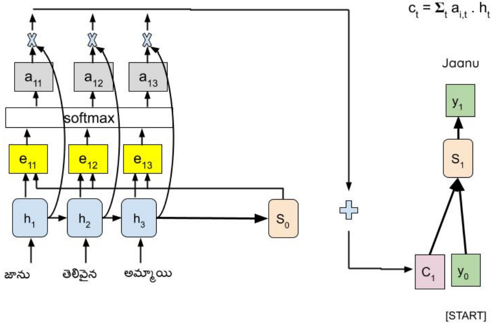

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All these operations are differentiable!
Attention is learned using backprop!!

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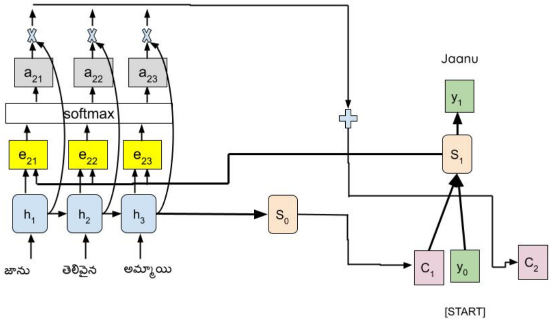

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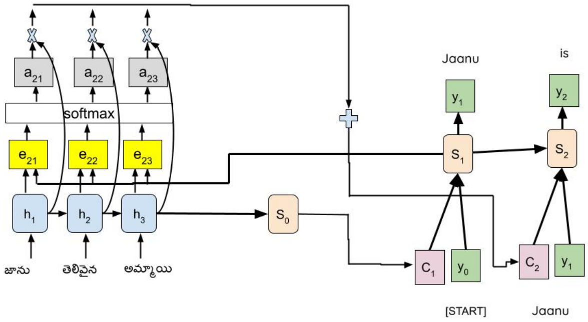

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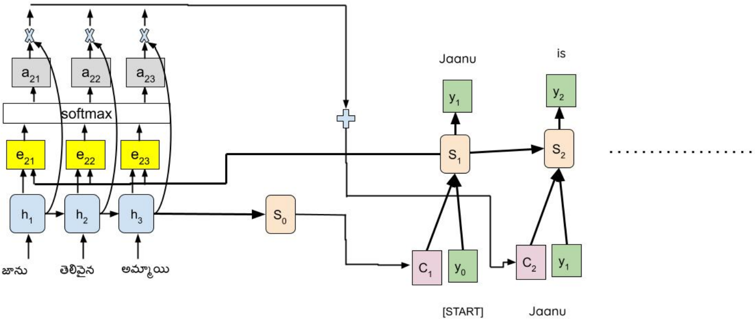

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- Employs a different context at each time step of decoding

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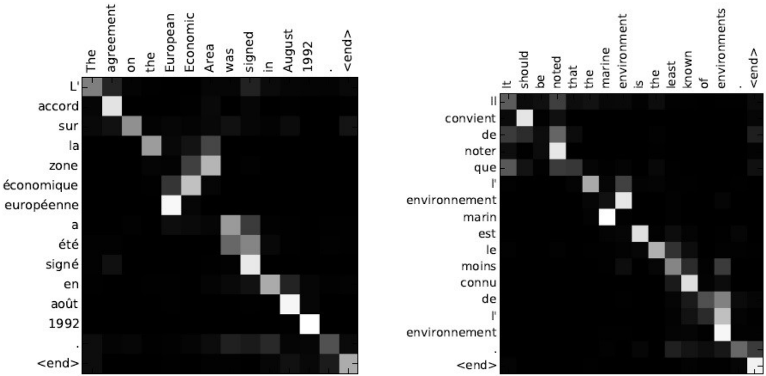
Encoder-Decoder for Machine Translation with Attention

- Employs a different context at each time step of decoding
- No more bottleneck-ing of the input
- Decoder can 'attend' to different portions of the input at each time step

Neural Machine Translation with aligning by Bahdanau et al. ICLR 2015

Encoder-Decoder for Machine Translation with Attention



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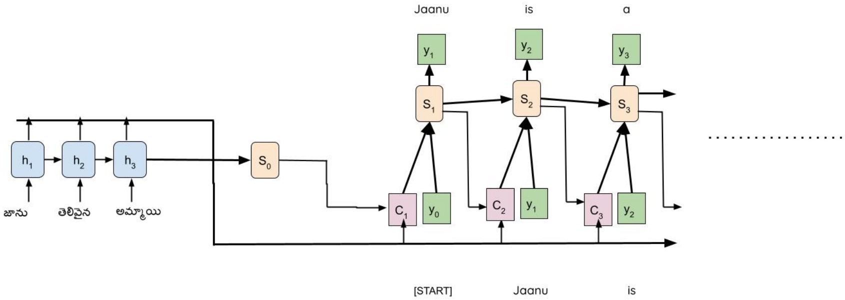

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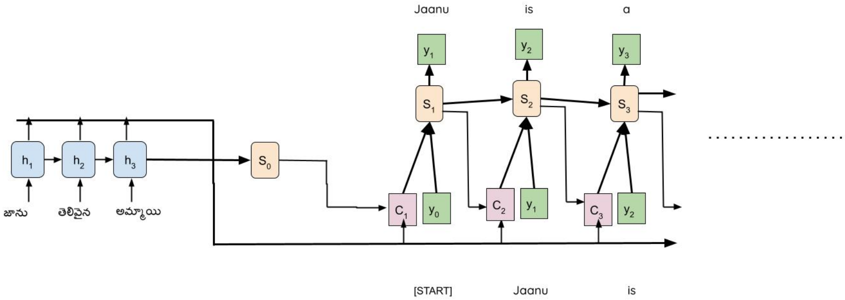
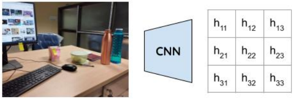


- Decoder doesn't consider the h_i to be an ordered set
- This architecture can be exploited to process a set of inputs h_i

Image captioning using RNNs with Attention



Show Attend and Tell by Xu et al. 2015

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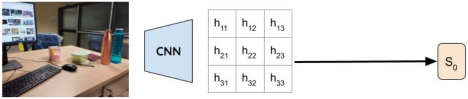

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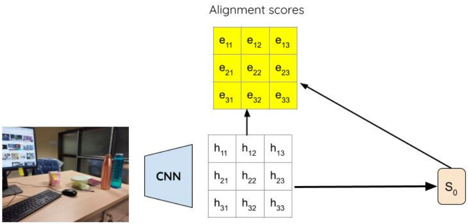

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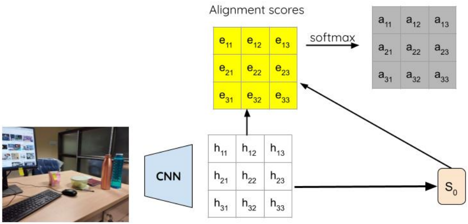

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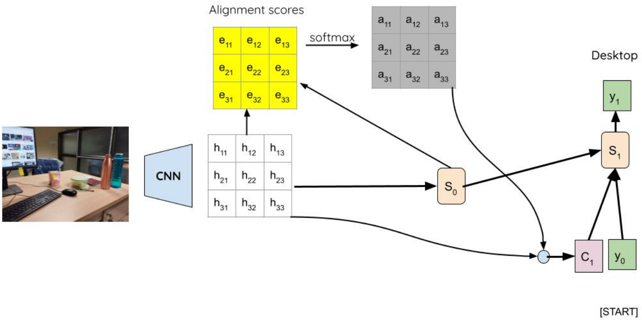

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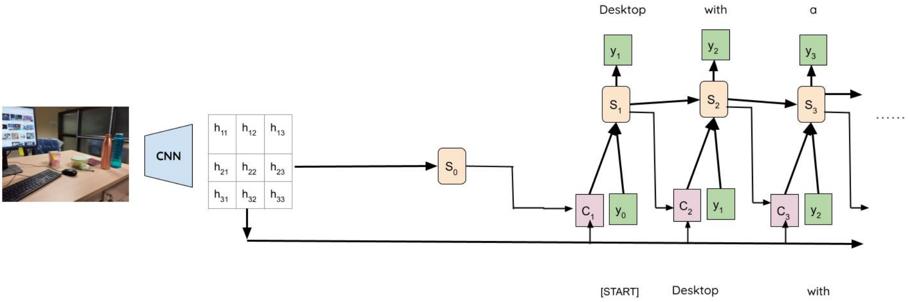

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Image captioning using RNNs with Attention

Figure 2. Attention over time. As the model generates each word, its attention changes to reflect the relevant parts of the image. "soft" (top row) vs "hard" (bottom row) attention. (Note that both models generated the same captions in this example.)

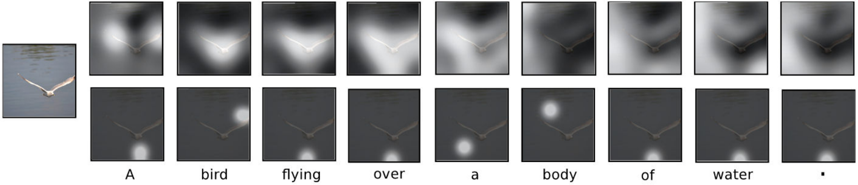

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Image captioning using RNNs with Attention

A woman is throwing a frisbee in a park.

A dog is standing on a hardwood floor.

A stop sign is on a road with a mountain in the background.

A little girl sitting on a bed with a teddy bear.

A group of people sitting on a boat in the water.

A giraffe standing in a forest with trees in the background.

Show Attend and Tell by Xu et al. 2015