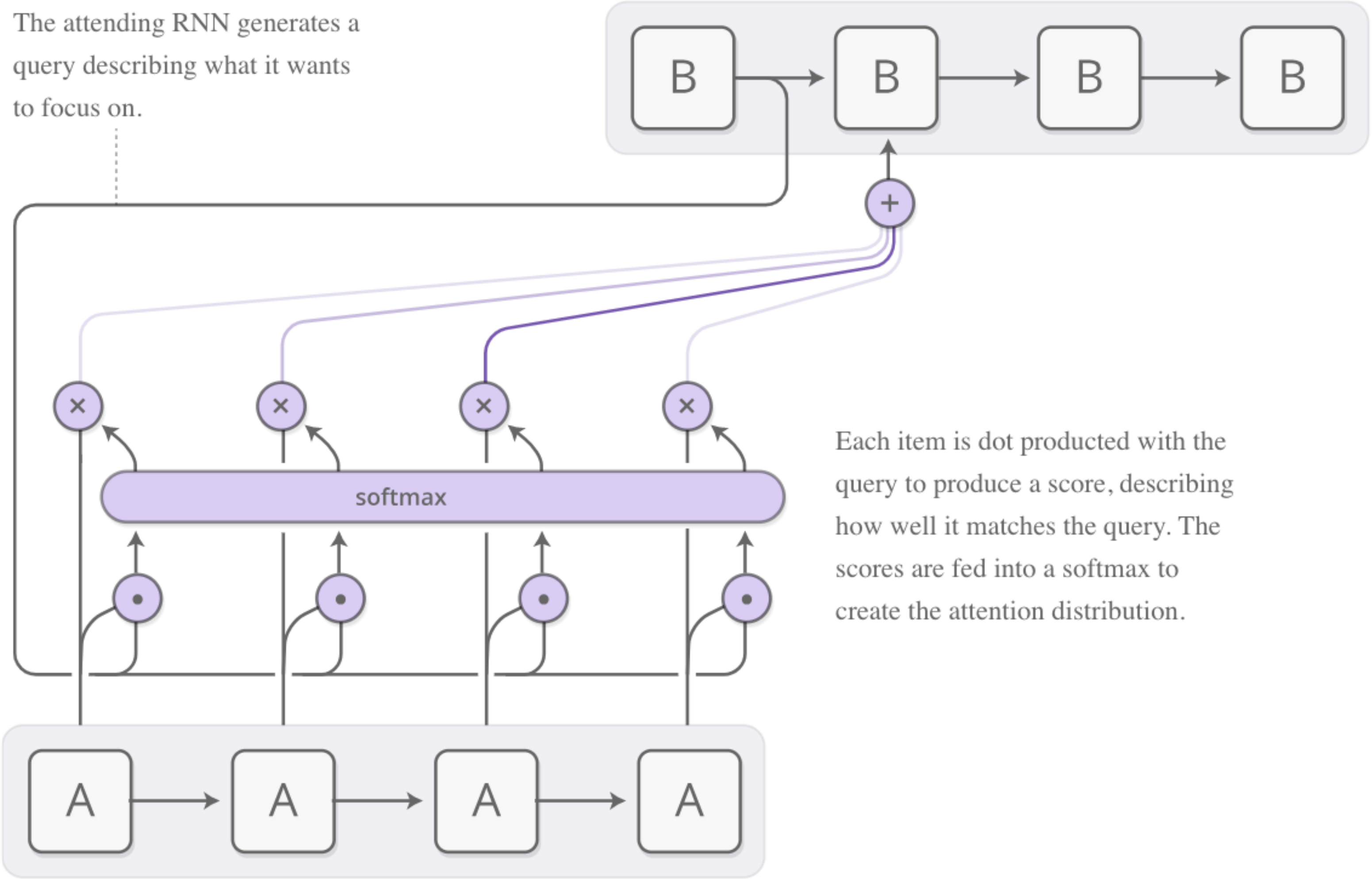
Sequence-to-sequence models with attention



Many slides adapted from [J. Johnson]

Outline

- Vanilla seq2seq with RNNs
- Seq2seq with RNNs and attention
- Image captioning with attention
- Convolutional seq2seq with attention

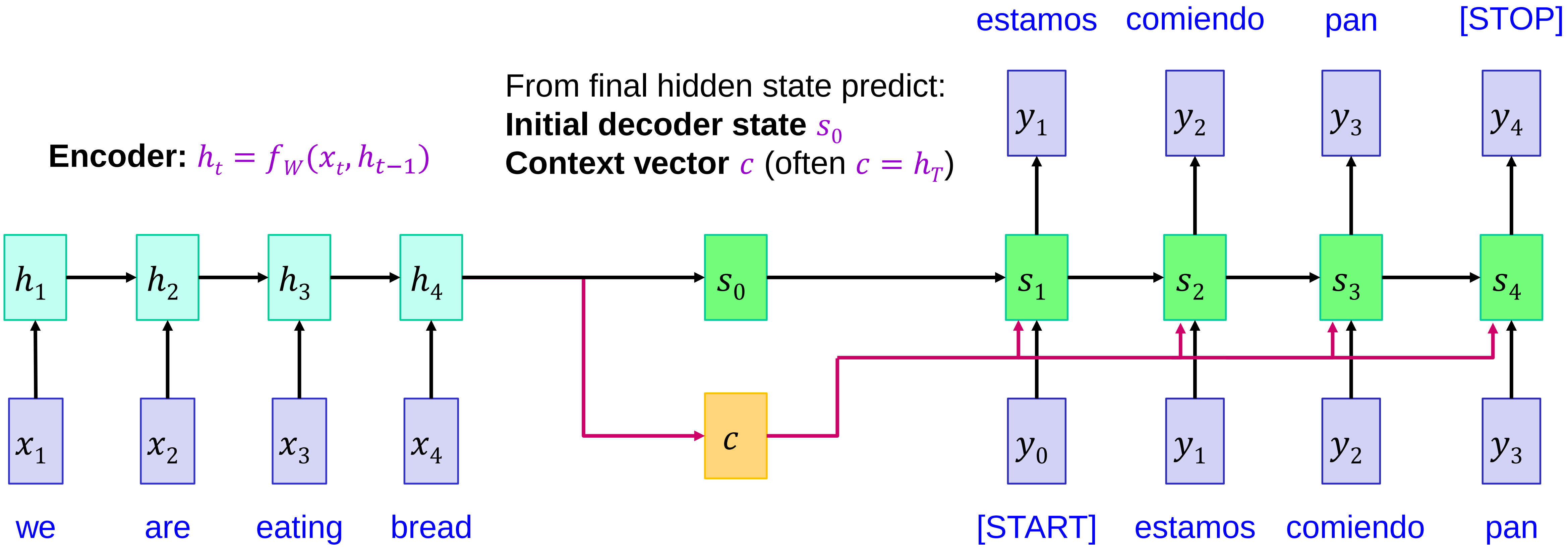
Sequence-to-sequence with RNNs

English to Spanish

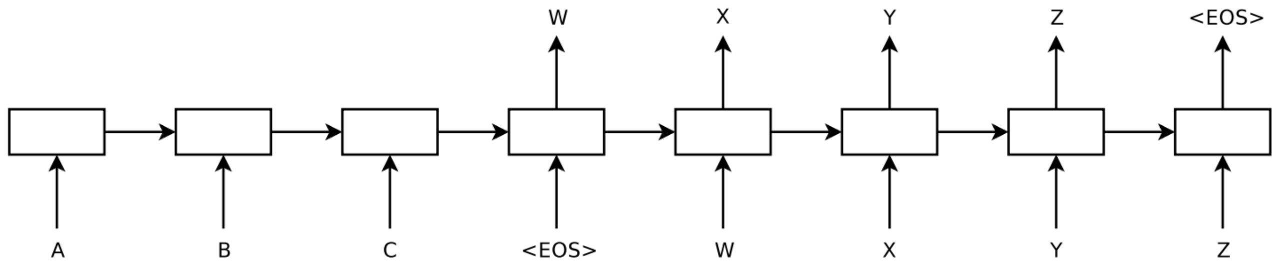
Decoder: $s_t = g_U(y_{t-1}, s_{t-1}, c)$

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

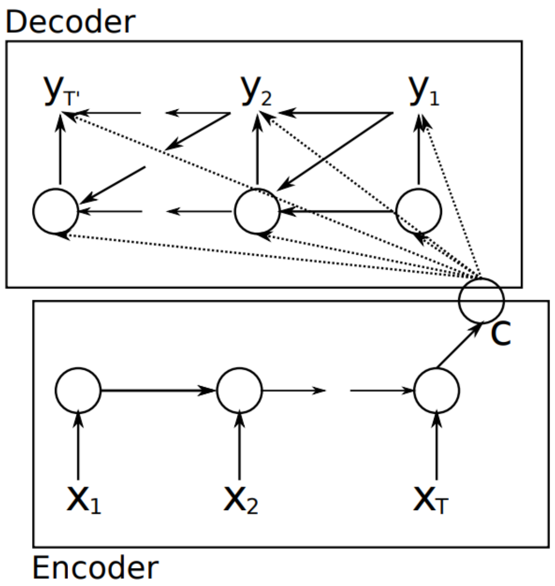
From final hidden state predict:
Initial decoder state s_0
Context vector c (often $c = h_T$)



Sequence-to-sequence with RNNs



I. Sutskever, O. Vinyals, Q. Le, Sequence to Sequence Learning with Neural Networks, NeurIPS 2014



K. Cho, B. Merrienboer, C. Gulcehre, F. Bougares, H. Schwenk, and Y. Bengio, Learning phrase representations using RNN encoder-decoder for statistical machine translation, ACL 2014

Sequence-to-sequence with RNNs

Decoder: $s_t = g_U(y_{t-1}, h_{t-1}, c)$

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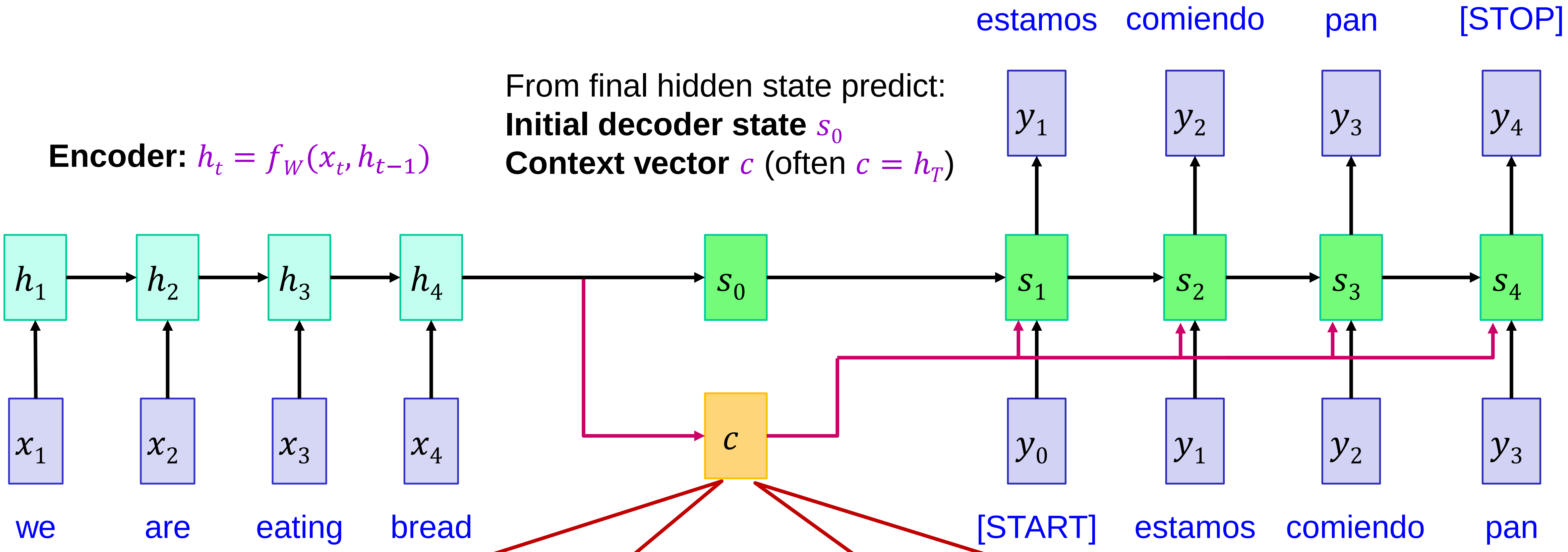


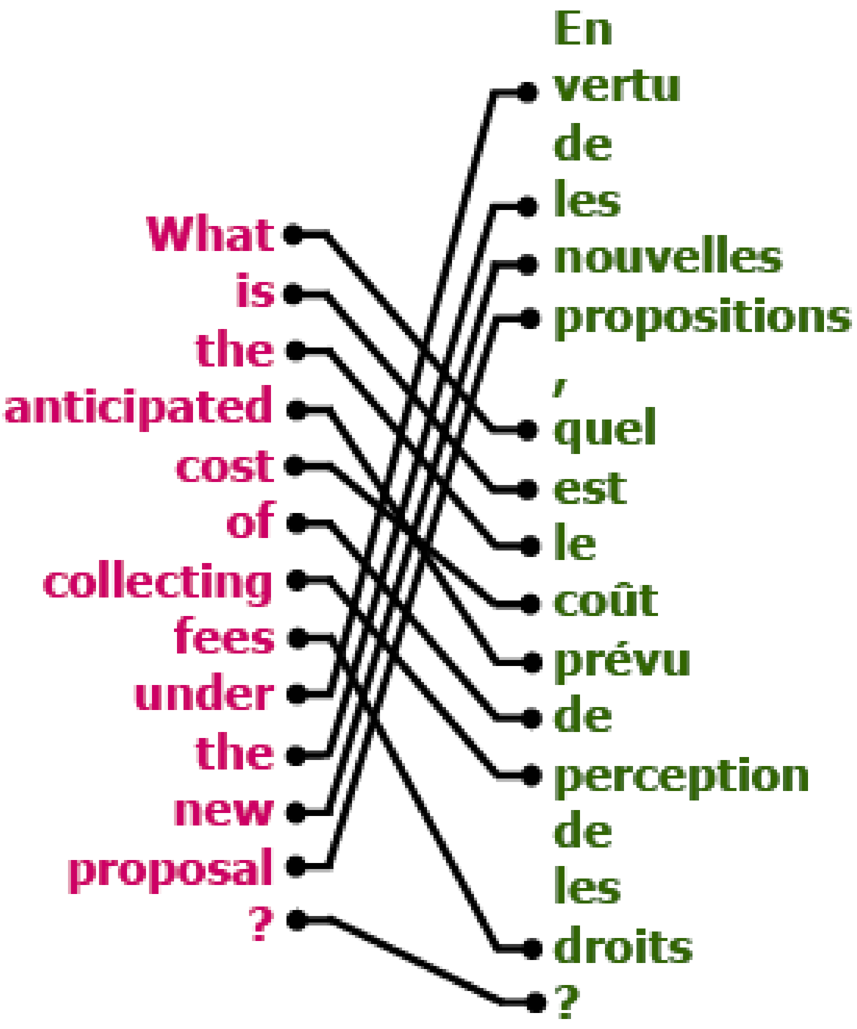
Problem: Input sequence bottlenecked through fixed-sized vector

Idea: use *new* context vector at each step of decoder!

A. Sutskever, O. Vinyals, Q. Le, Sequence to sequence learning with neural networks, NeurIPS 2014

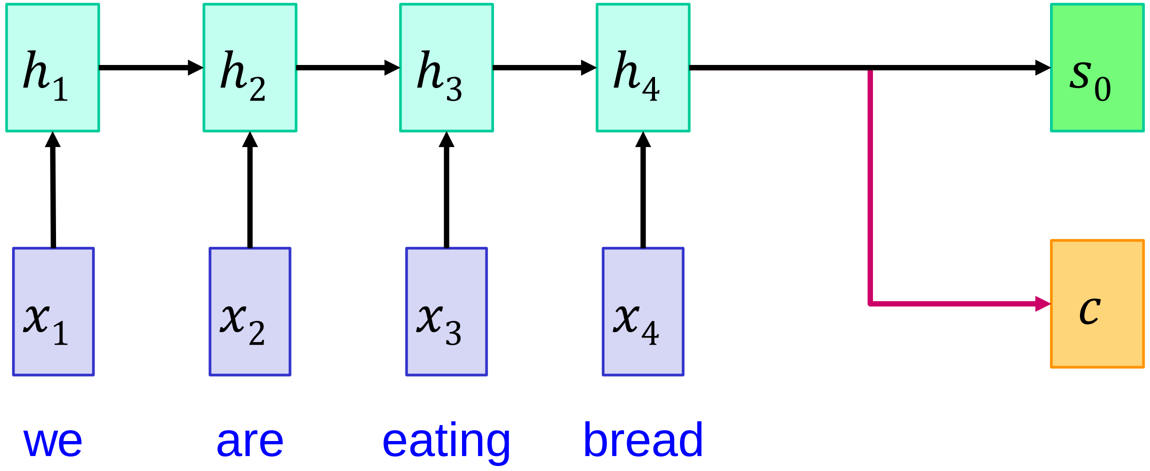
Sequence-to-sequence with RNNs *and attention*

- Intuition: translation requires *alignment*

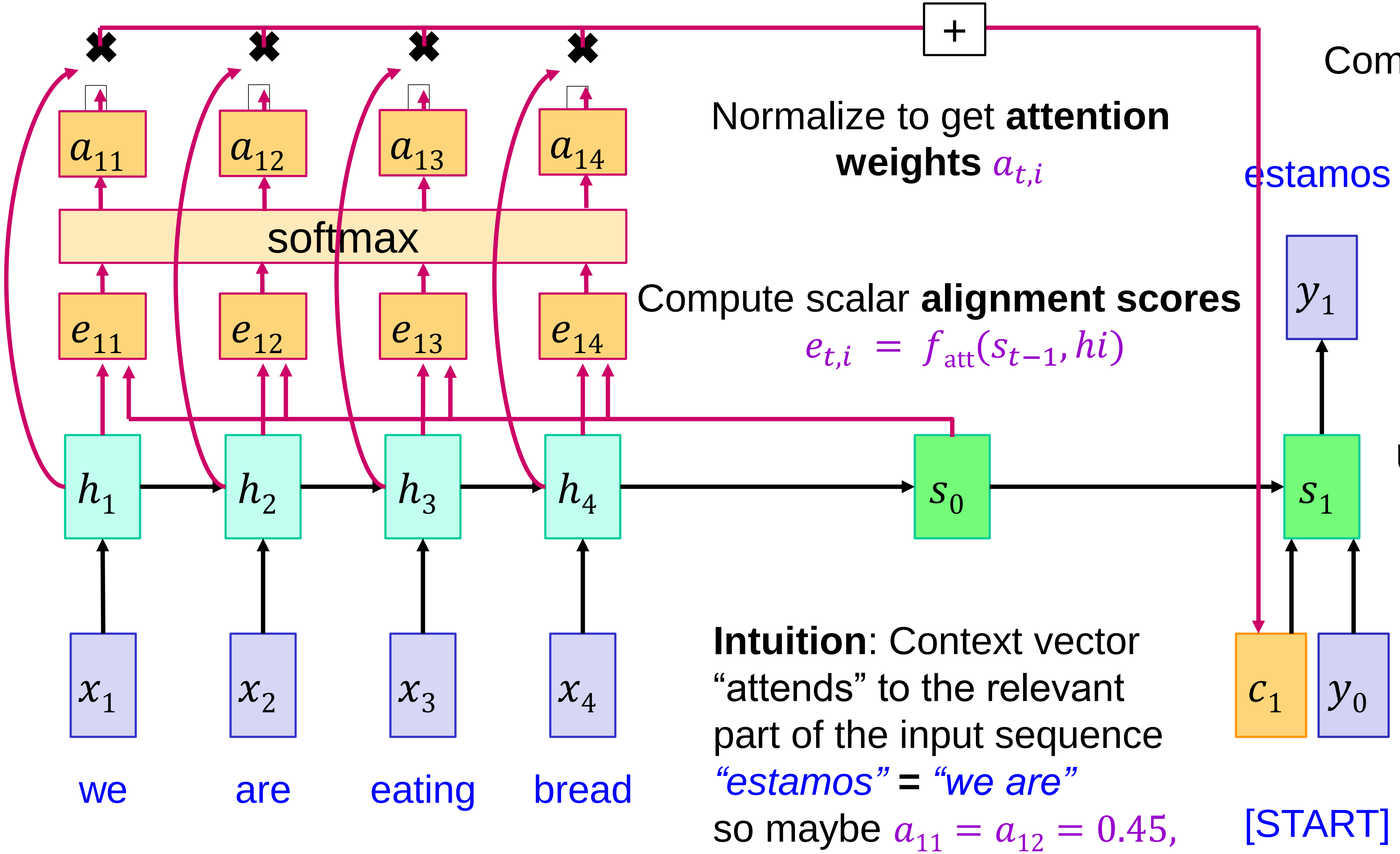


Sequence-to-sequence with RNNs and attention

- At each timestep of decoder, context vector "looks at" different parts of the input sequence



Sequence-to-sequence with RNNs and attention



Normalize to get **attention weights** $a_{t,i}$

Compute scalar **alignment scores**
$e_{t,i} = f_{\text{att}}(s_{t-1}, hi)$

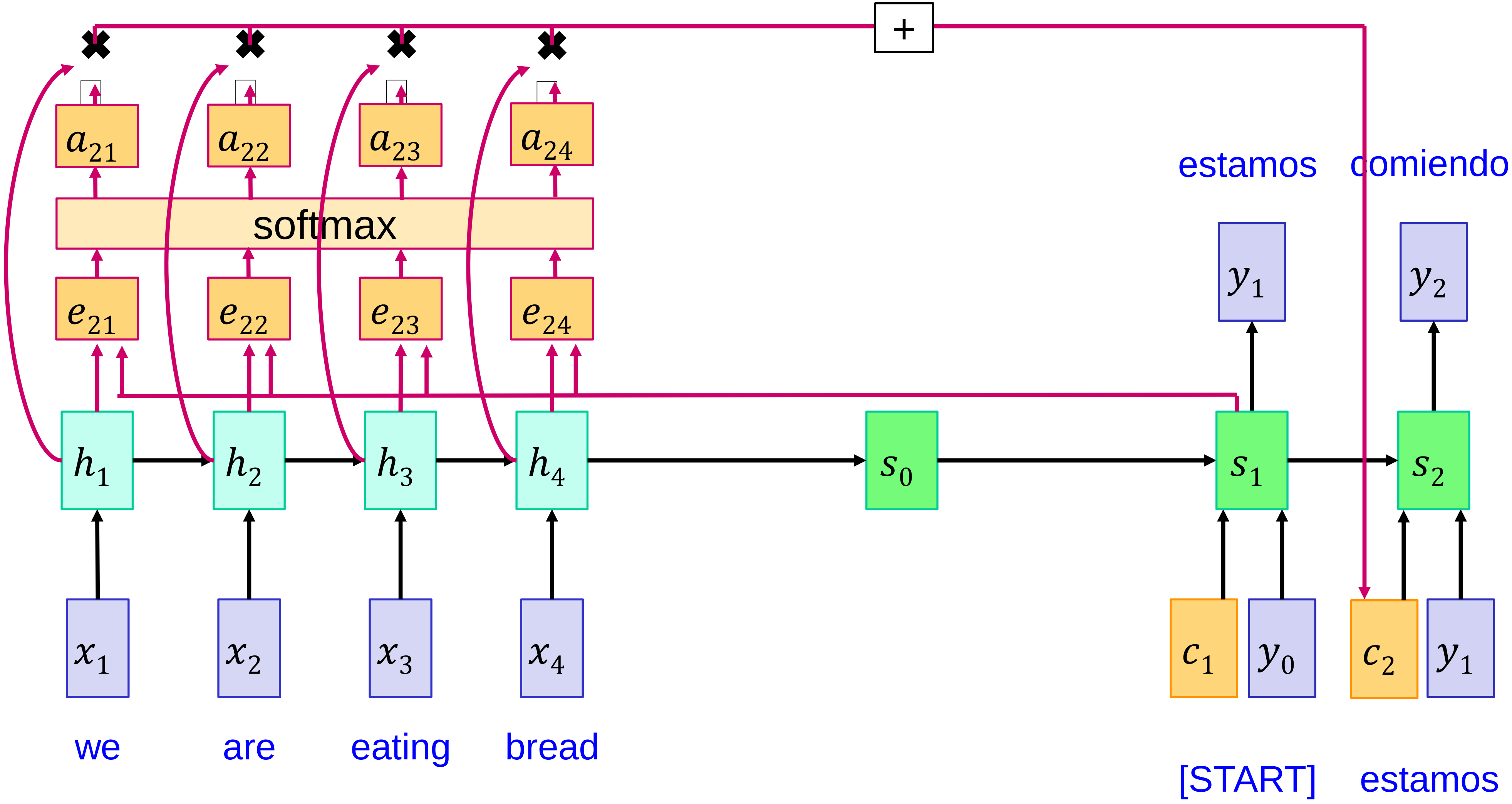
Compute **context vector** as
$c_t = \sum_i a_{t,i} h_i$

Use context vector in decoder:
$s_t = g_U(y_{t-1}, s_{t-1}, c_t)$

Intuition: Context vector "attends" to the relevant part of the input sequence
"estamos" = *"we are"*
so maybe $a_{11} = a_{12} = 0.45$,
$a_{13} = a_{14} = 0.05$

D. Bahdanau, K. Cho, Y. Bengio, [Neural Machine Translation by Jointly Learning to Align and Translate](), ICLR 2015

Sequence-to-sequence with RNNs and attention

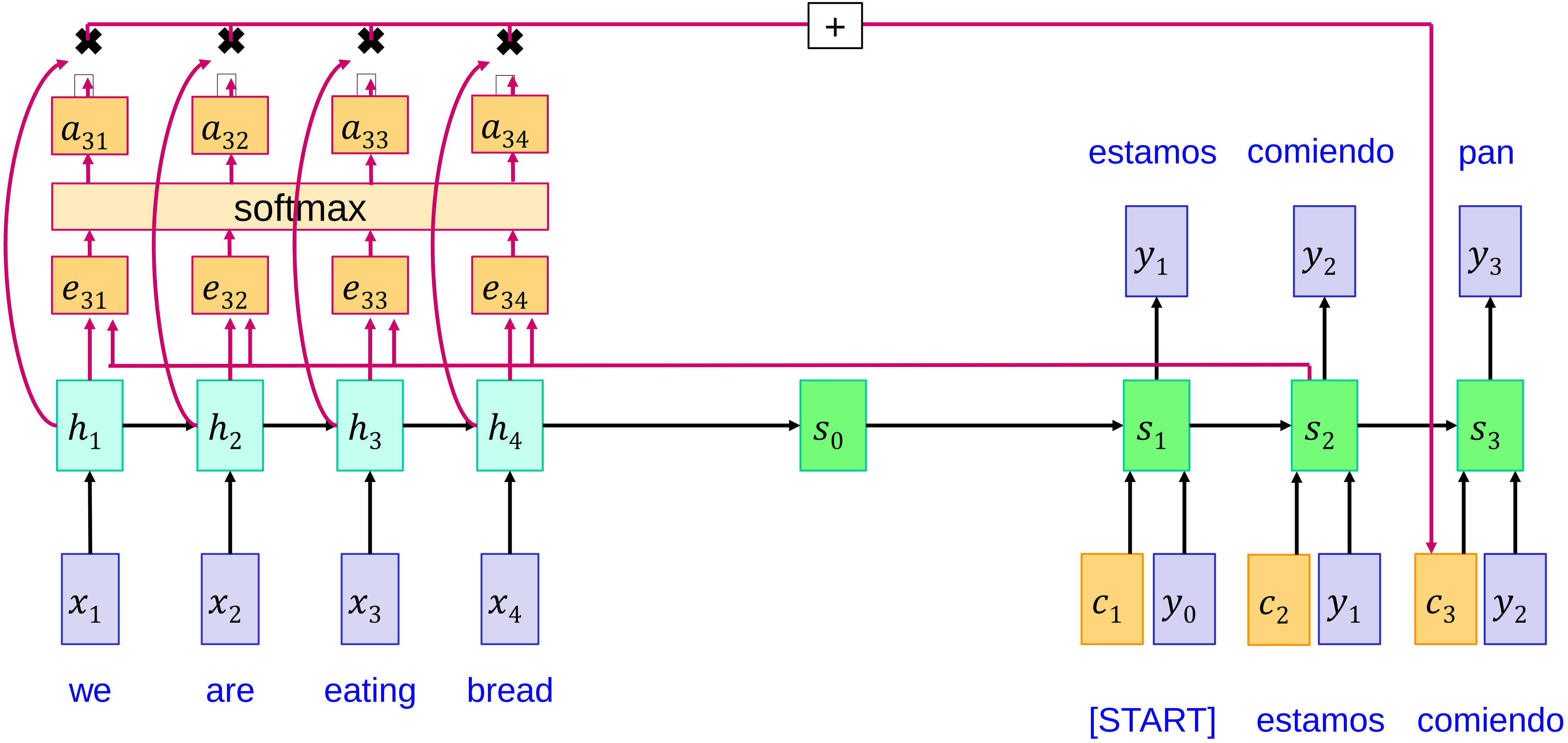


Use c_2 to compute s_2, y_2

Repeat: Use s_1 to compute new context vector c_2

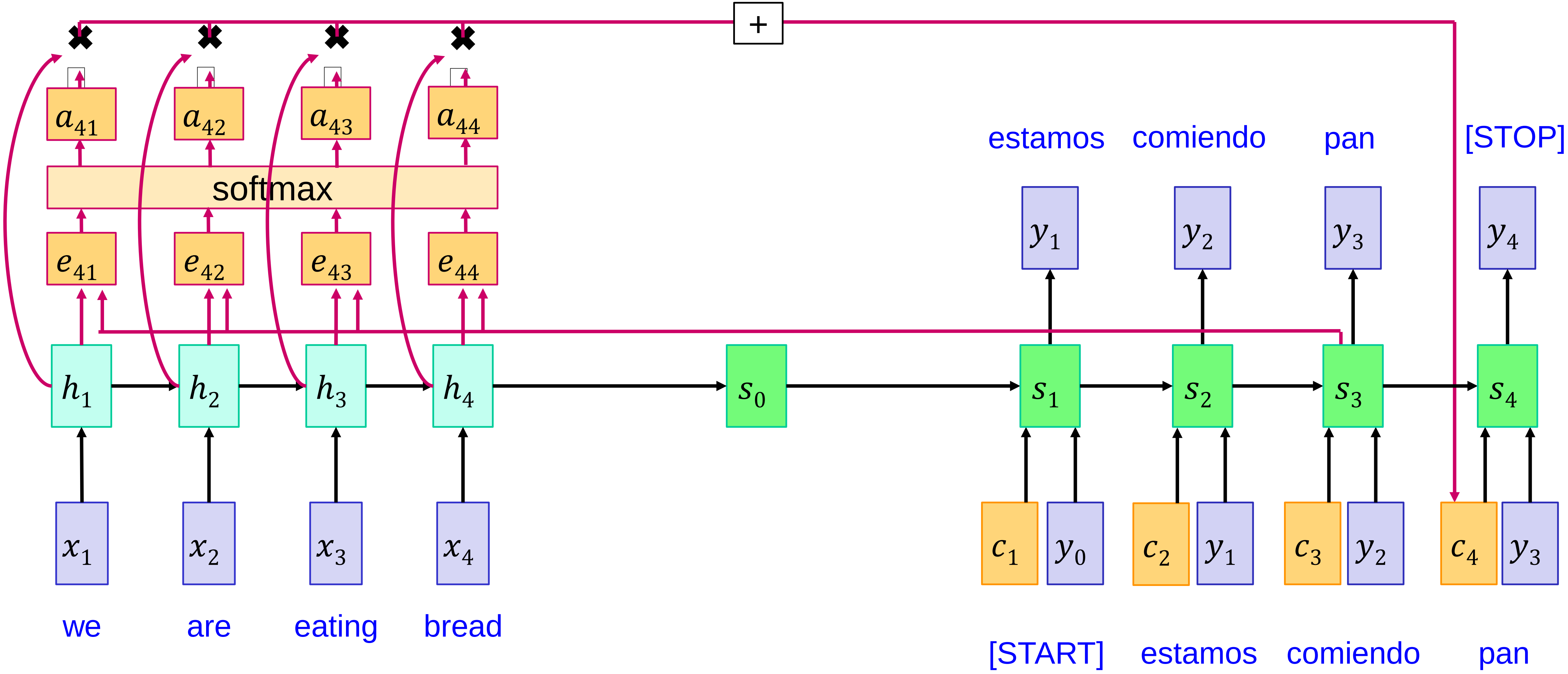
D. Bahdanau, K. Cho, Y. Bengio, [Neural Machine Translation by Jointly Learning to Align and Translate](), ICLR 2015

Sequence-to-sequence with RNNs and attention



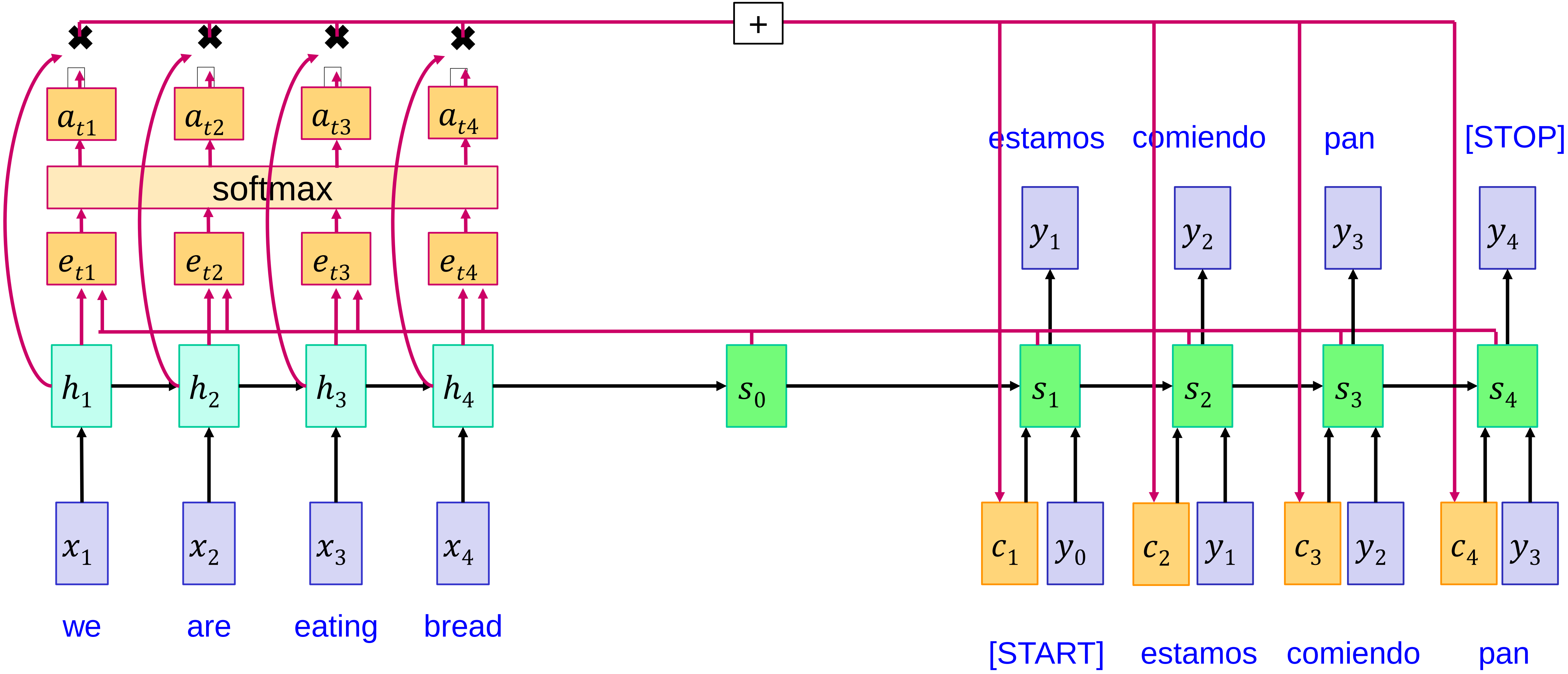
D. Bahdanau, K. Cho, Y. Bengio, [Neural Machine Translation by Jointly Learning to Align and Translate](), ICLR 2015

Sequence-to-sequence with RNNs and attention



D. Bahdanau, K. Cho, Y. Bengio, [Neural Machine Translation by Jointly Learning to Align and Translate](), ICLR 2015

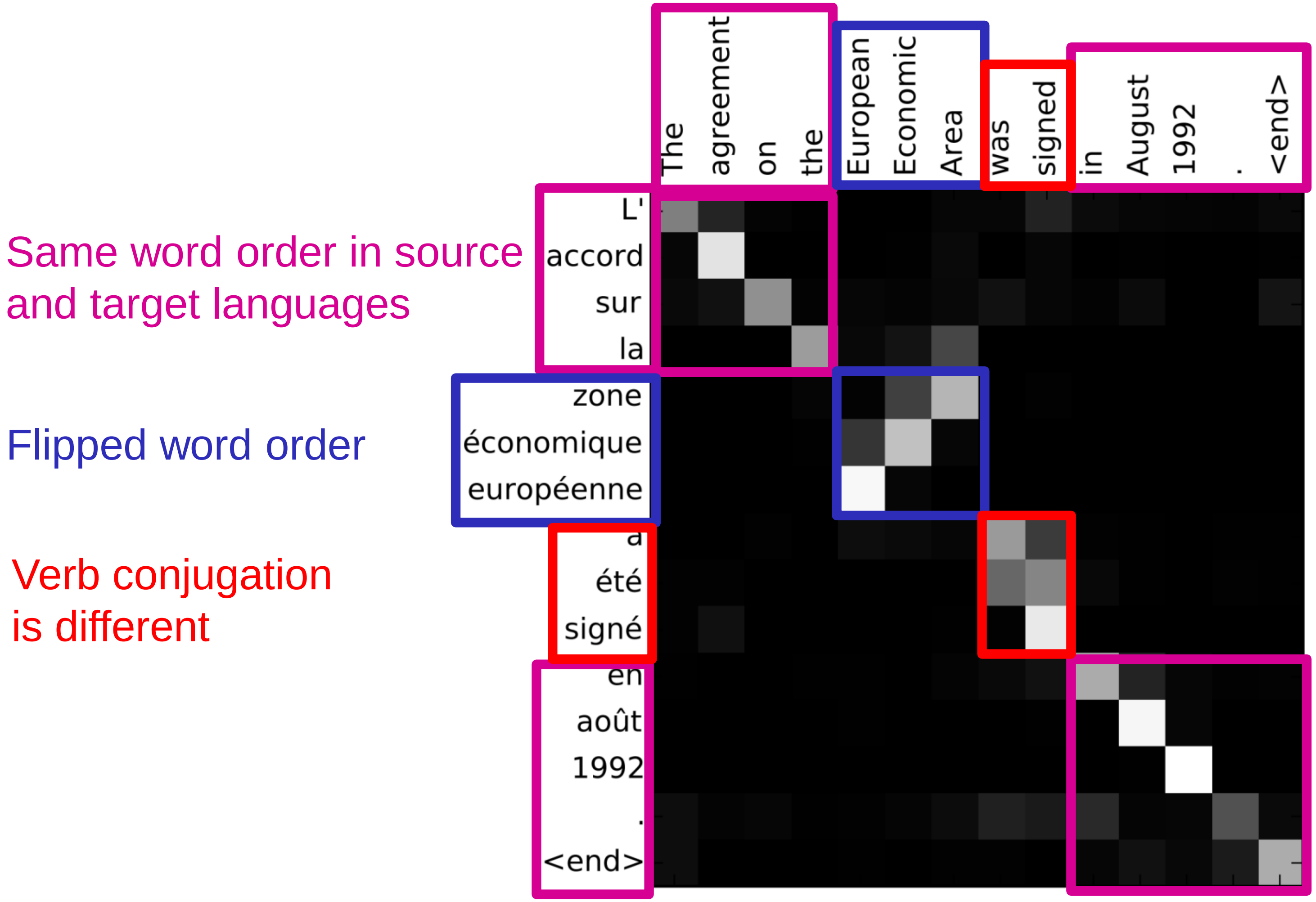
Sequence-to-sequence with RNNs and attention



D. Bahdanau, K. Cho, Y. Bengio, Neural Machine Translation by Jointly Learning to Align and Translate, ICLR 2015

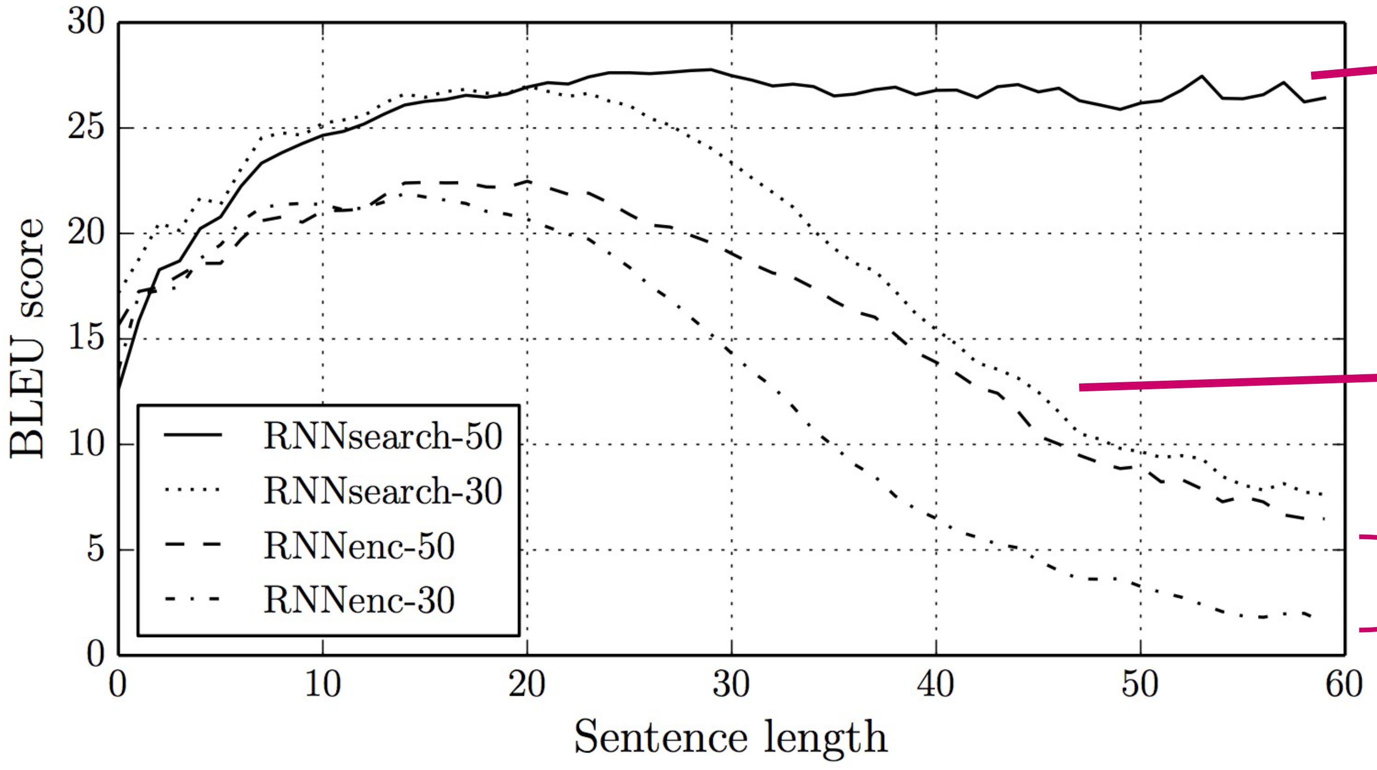
Sequence-to-sequence with RNNs and attention

- Visualizing attention weights:



D. Bahdanau, K. Cho, Y. Bengio, [Neural Machine Translation by Jointly Learning to Align and Translate](), ICLR 2015

Quantitative evaluation



With attention (trained with sentence length <= 50)

With attention (trained with sentence length <= 30)

No attention

D. Bahdanau, K. Cho, Y. Bengio, [Neural Machine Translation by Jointly Learning to Align and Translate](), ICLR 2015

Google Neural Machine Translation (GNMT)

Google's Neural Machine Translation System: Bridging the Gap between Human and Machine Translation

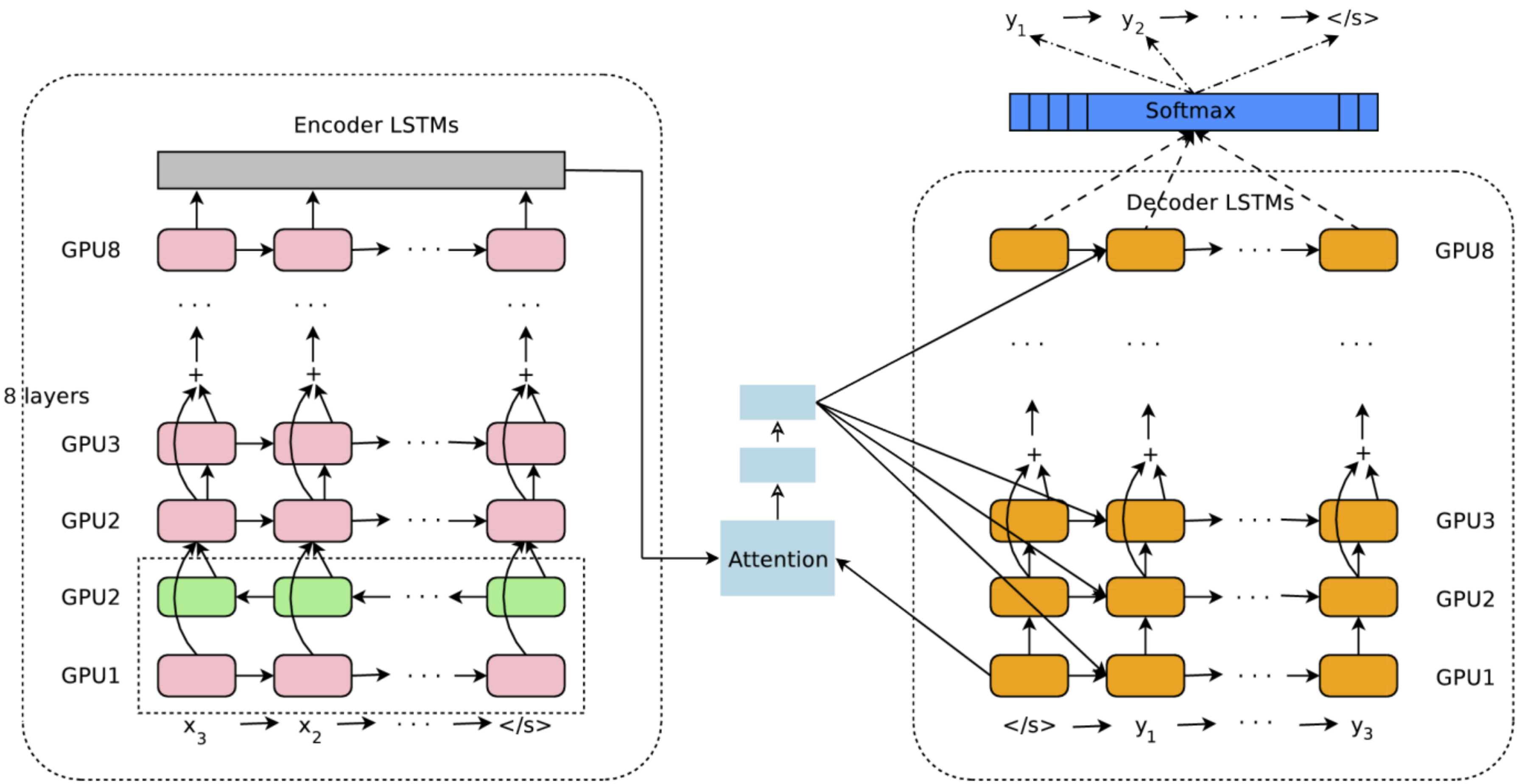
Yonghui Wu, Mike Schuster, Zhifeng Chen, Quoc V. Le, Mohammad Norouzi
yonghui,schuster,zhifengc,qvl,mnorouzi@google.com

Wolfgang Macherey, Maxim Krikun, Yuan Cao, Qin Gao, Klaus Macherey, Jeff Klingner, Apurva Shah, Melvin Johnson, Xiaobing Liu, Łukasz Kaiser, Stephan Gouws, Yoshikiyo Kato, Taku Kudo, Hideto Kazawa, Keith Stevens, George Kurian, Nishant Patil, Wei Wang, Cliff Young, Jason Smith, Jason Riesa, Alex Rudnick, Oriol Vinyals, Greg Corrado, Macduff Hughes, Jeffrey Dean

Y. Wu et al., Google's Neural Machine Translation System: Bridging the Gap between Human and Machine Translation, arXiv 2016

https://www.nytimes.com/2016/12/14/magazine/the-great-ai-awakening.html

Google Neural Machine Translation (GNMT)



Y. Wu et al., [Google's Neural Machine Translation System: Bridging the Gap between Human and Machine Translation](), arXiv 2016

Google Neural Machine Translation (GNMT)

- **Standard training objective:** maximize log-likelihood of ground truth output given input:

$$\sum_i \log P_W(Y_i^* | X_i)$$

  - Not related to task-specific reward function (e.g., BLEU score)
  - Does not encourage "better" incorrect sentences to get better likelihood
- **Refinement objective:** expectation of rewards over possible predicted sentences Y:

$$\sum_i \sum_Y P_W(Y | X_i)\, R(Y, Y_i^*)$$

  - Use variant of BLEU score to compute reward
  - Reward is not differentiable -- need *reinforcement learning* to train (initialize with ML-trained model)

Google Neural Machine Translation (GNMT)

- Human evaluation results on production data (500 randomly sampled sentences from Wikipedia and news websites)

Table 10: Mean of side-by-side scores on production data

	PBMT	GNMT	Human	Relative Improvement
English → Spanish	4.885	5.428	5.550	87%
English → French	4.932	5.295	5.496	64%
English → Chinese	4.035	4.594	4.987	58%
Spanish → English	4.872	5.187	5.372	63%
French → English	5.046	5.343	5.404	83%
Chinese → English	3.694	4.263	4.636	60%

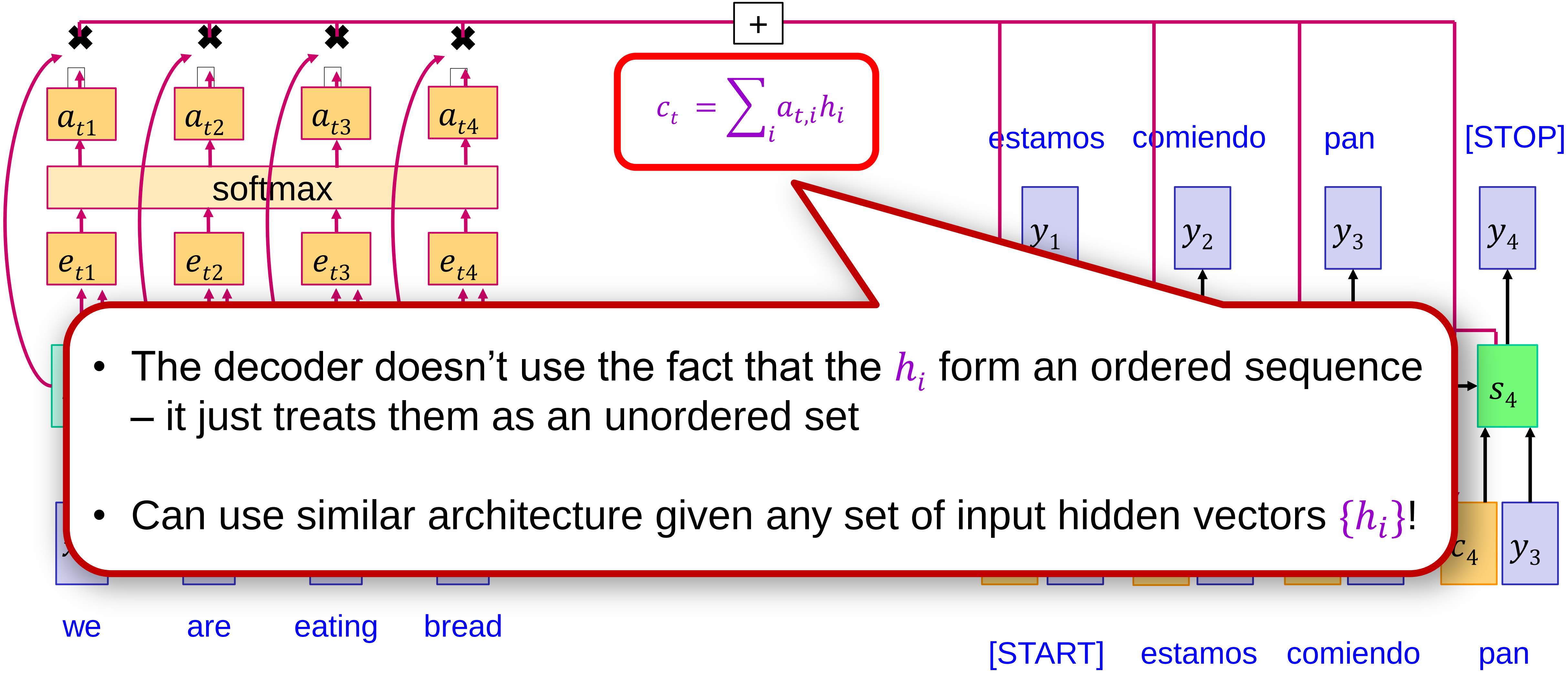
Side-by-side scores: range from 0 (“completely nonsense translation”) to 6 (“perfect translation”), produced by human raters fluent in both languages

PBMT: Translation by phrase-based statistical translation system used by Google
GNMT: Translation by GNMT system
Human: Translation by humans fluent in both languages

Outline

- Vanilla seq2seq with RNNs
- Seq2seq with RNNs and attention
- Image captioning with attention

Generalizing attention



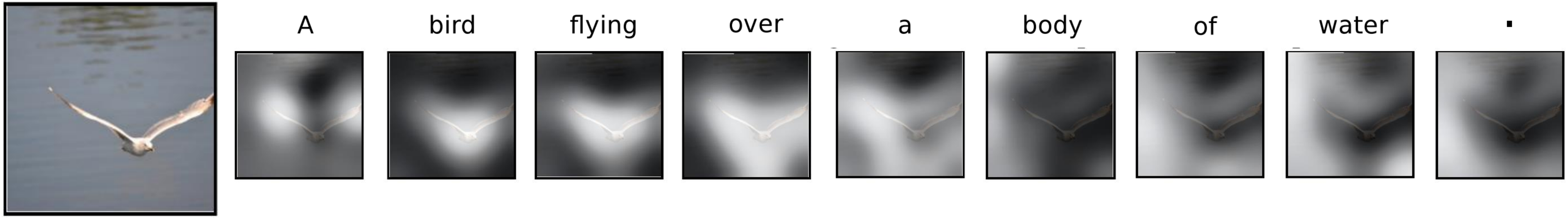
$$c_t = \sum_i a_{t,i} h_i$$

- The decoder doesn't use the fact that the h_i form an ordered sequence – it just treats them as an unordered set

- Can use similar architecture given any set of input hidden vectors $\{h_i\}$!

Image captioning with RNNs and attention

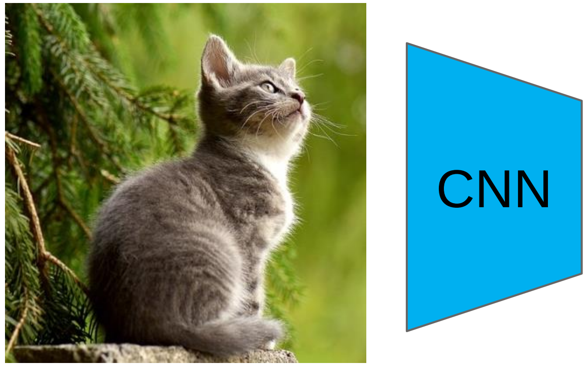
- Idea: pay attention to different parts of the image when generating different words
- Automatically learn this grounding of words to image regions without direct supervision

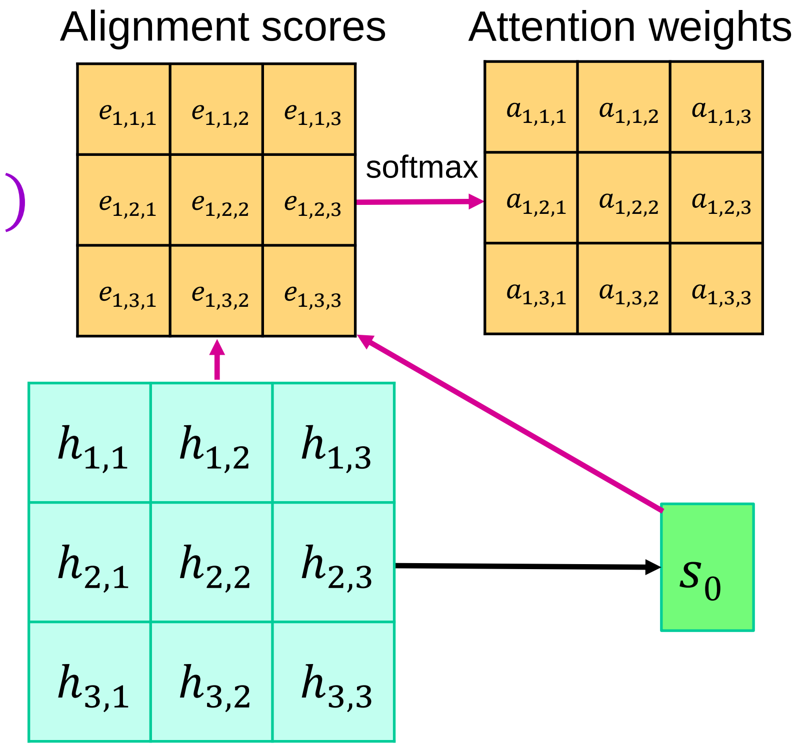


K. Xu et al., [Show, Attend and Tell: Neural Image Caption Generation with Visual Attention](), ICML 2015

Image captioning with RNNs and attention

$$e_{t,i,j} = f_{\text{att}}(s_{t-1}, h_{i,j})$$



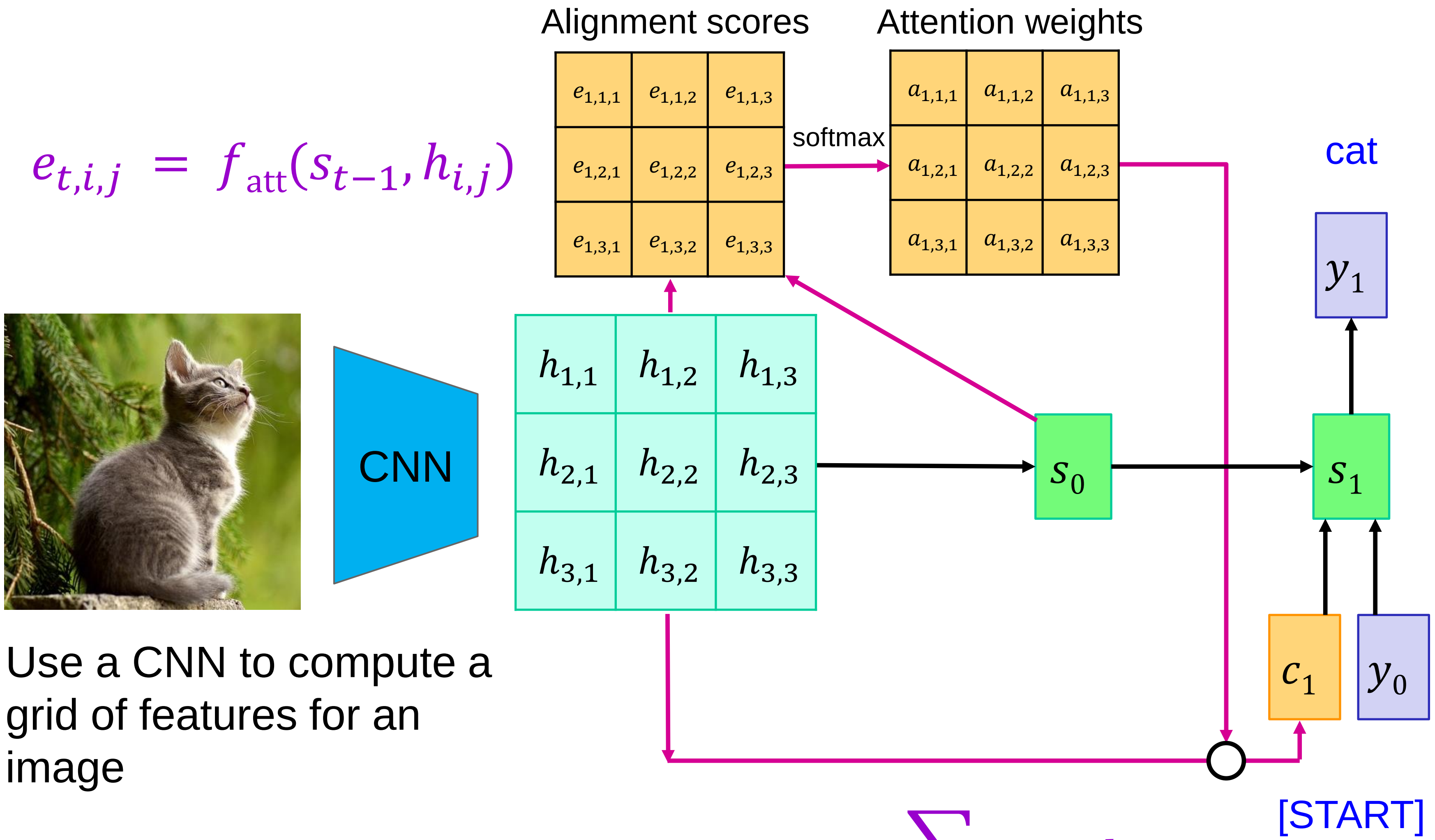


Use a CNN to compute a grid of features for an image

K. Xu et al., [Show, Attend and Tell: Neural Image Caption Generation with Visual Attention](), ICML 2015

Image captioning with RNNs and attention

$$e_{t,i,j} = f_{\text{att}}(s_{t-1}, h_{i,j})$$



Use a CNN to compute a grid of features for an image

$$c_t = \sum_i a_{t,i,j} h_i$$

Image captioning with RNNs and attention

$$e_{t,i,j} = f_{\text{att}}(s_{t-1}, h_{i,j})$$

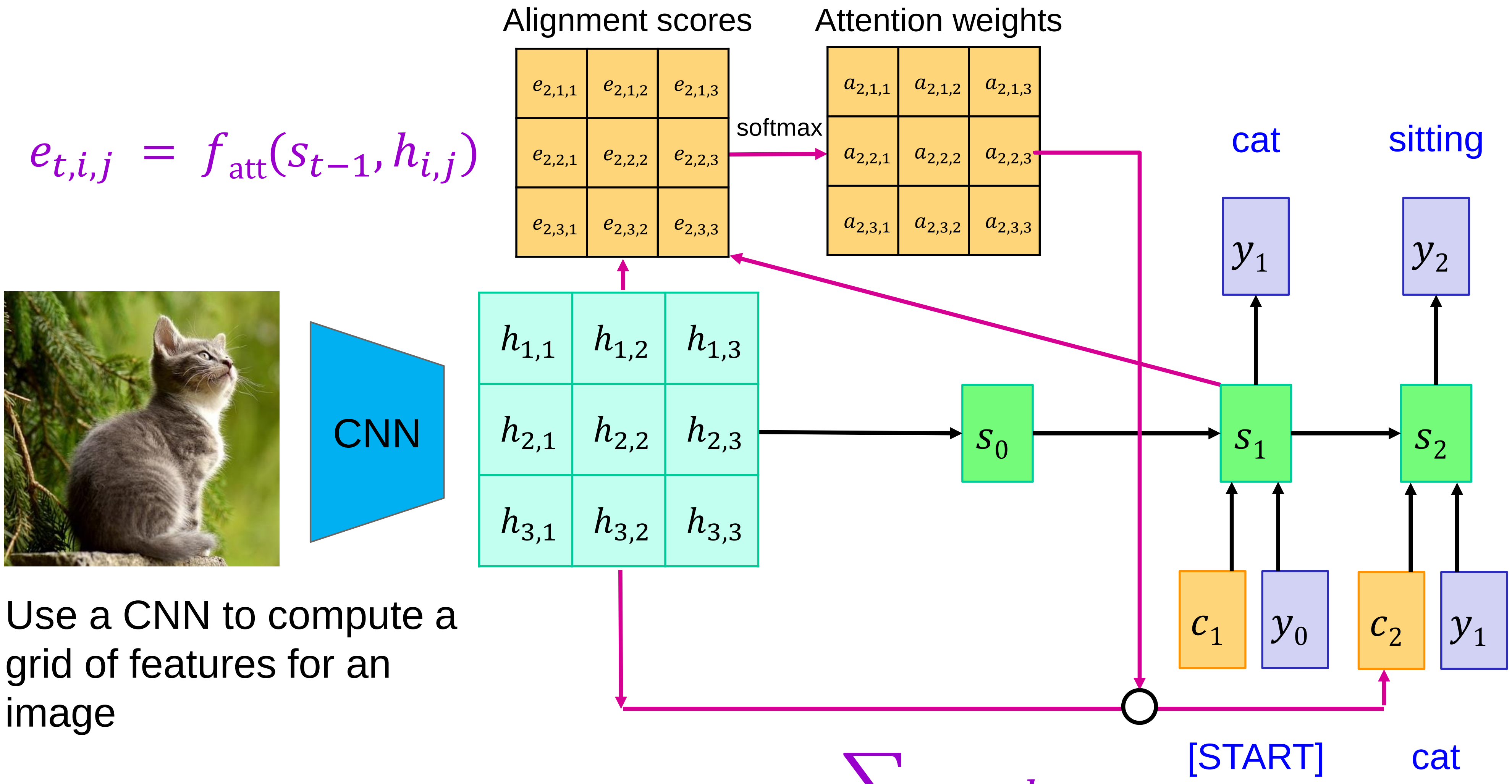


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Image captioning with RNNs and attention

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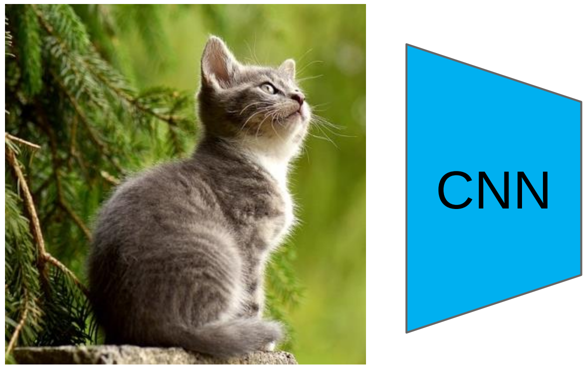
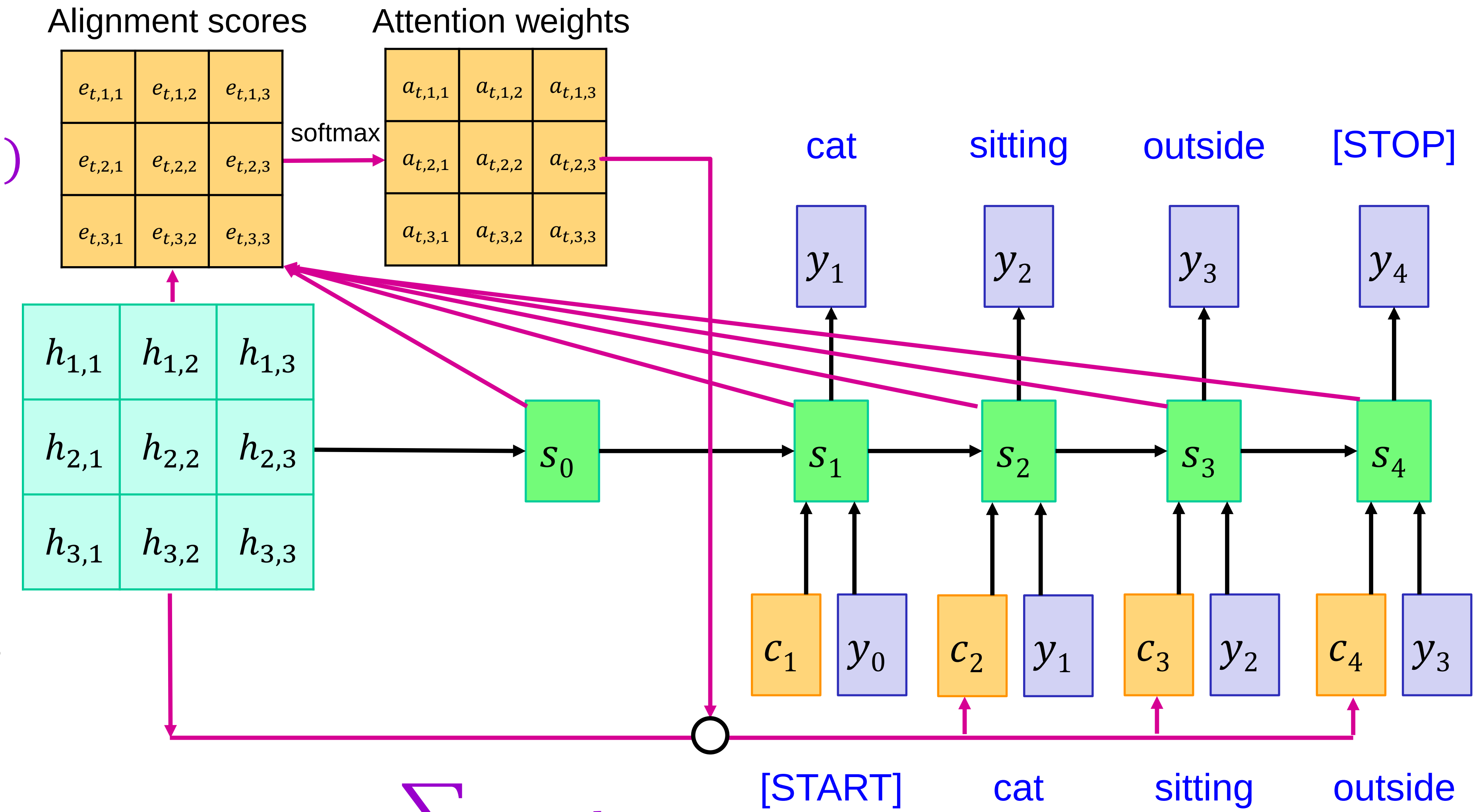




Use a CNN to compute a grid of features for an image

$$c_t = \sum_i a_{t,i,j} h_i$$

Each time step of decoder uses a different context vector that looks at different parts of the input image

Example results

- Good captions

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.

Example results

- Mistakes

A large white bird standing in a forest.

A woman holding a clock in her hand.

A man wearing a hat and
a hat on a skateboard.

A person is standing on a beach
with a surfboard.

A woman is sitting at a table
with a large pizza.

A man is talking on his cell phone
while another man watches.

Quantitative results

Dataset	Model	BLEU-1	BLEU-2	BLEU-3	BLEU-4	METEOR
Flickr8k	Google NIC	63	41	27	-	-
	Soft-Attention	**67**	44.8	29.9	19.5	18.93
	Hard-Attention	**67**	**45.7**	**31.4**	**21.3**	**20.30**
Flickr30k	Google NIC	66.3	42.3	27.7	18.3	-
	Soft-Attention	66.7	43.4	28.8	19.1	**18.49**
	Hard-Attention	**66.9**	**43.9**	**29.6**	**19.9**	18.46
COCO	Google NIC	66.6	46.1	32.9	24.6	-
	Soft-Attention	70.7	49.2	34.4	24.3	**23.90**
	Hard-Attention	**71.8**	**50.4**	**35.7**	**25.0**	23.04

Soft attention is when we calculate the context vector as a weighted sum of the encoder hidden states.

Hard attention is when, instead of weighted average of all hidden states, we use **attention** scores to select a single hidden state.

Source

X, Attend, and Y

“**Show, attend, and tell**” *(Xu et al, ICML 2015)*
Look at image, attend to image regions, produce question

“**Ask, attend, and answer**” *(Xu and Saenko, ECCV 2016)*
“**Show, ask, attend, and answer”** *(Kazemi and Elqursh, 2017)*
Read text of question, attend to image regions, produce answer

“**Listen, attend, and spell**” *(Chan et al, ICASSP 2016)*
Process raw audio, attend to audio regions while producing text

“**Listen, attend, and walk**” *(Mei et al, AAAI 2016)*
Process text, attend to text regions, output navigation commands

“**Show, attend, and interact**” *(Qureshi et al, ICRA 2017)*
Process image, attend to image regions, output robot control commands

“**Show, attend, and read**” *(Li et al, AAAI 2019)*
Process image, attend to image regions, output text

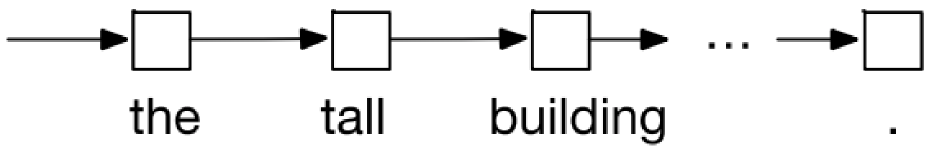
Source: [J. Johnson]

Outline

- Vanilla seq2seq with RNNs
- Seq2seq with RNNs and attention
- Image captioning with attention
- Convolutional seq2seq with attention

Recurrent vs. convolutional sequence models

- **Recurrent models:**
  - Treat input as ordered sequence (inherently sequential processing)
  - Build up context using the hidden vector



- **Convolutional models:**
  - Treat input as a grid indexed by time and feature dimension
  - Build up context using multiple layers of convolutions
  - Processing can be parallel at training time, but convolutions must be *causal*

(A filter is called causal if the filter output does not depend on future inputs.)

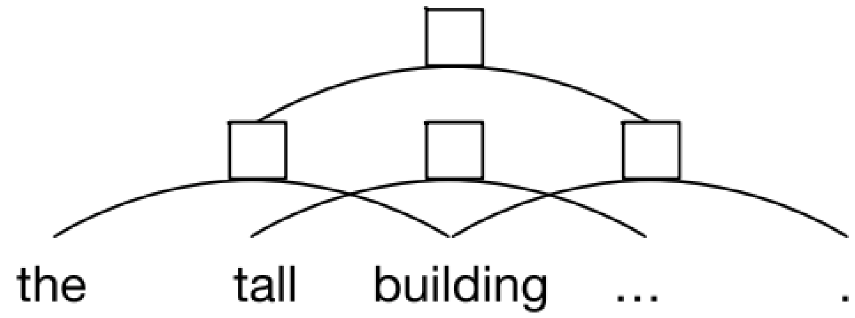


Image source (Facebook AI Research)

WaveNet

- Goal: generate raw audio
  - Represented as sequence of 16-bit integer values (can be quantized to 256 discrete levels), 16K samples per second
- Applications: text-to-speech, music generation
  - Also works for speech recognition

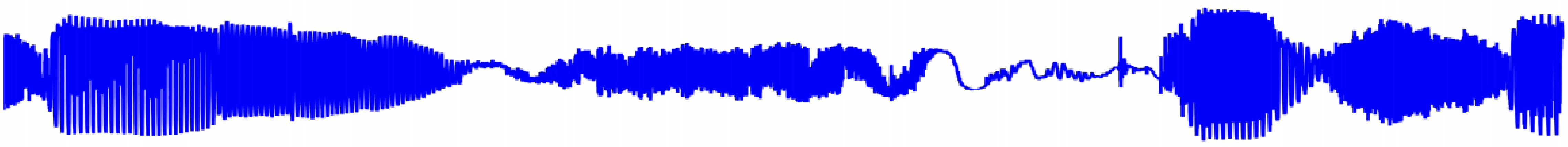


Figure 1: A second of generated speech.

A. van den Oord et al., [WaveNet: A generative model for raw audio](), arXiv 2016

WaveNet

- Training time: compute predictions of all timesteps in parallel (conditioned on ground truth)

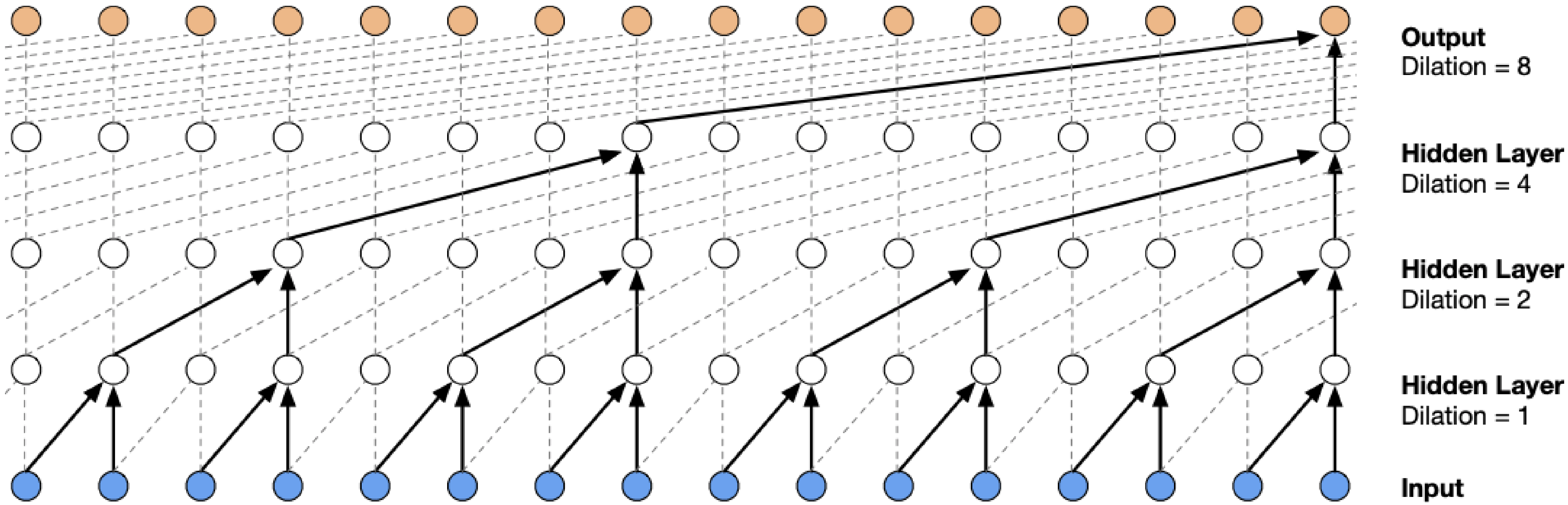


Image source

WaveNet

- Test time: feed each predicted sample back into the model to make prediction at next timestep

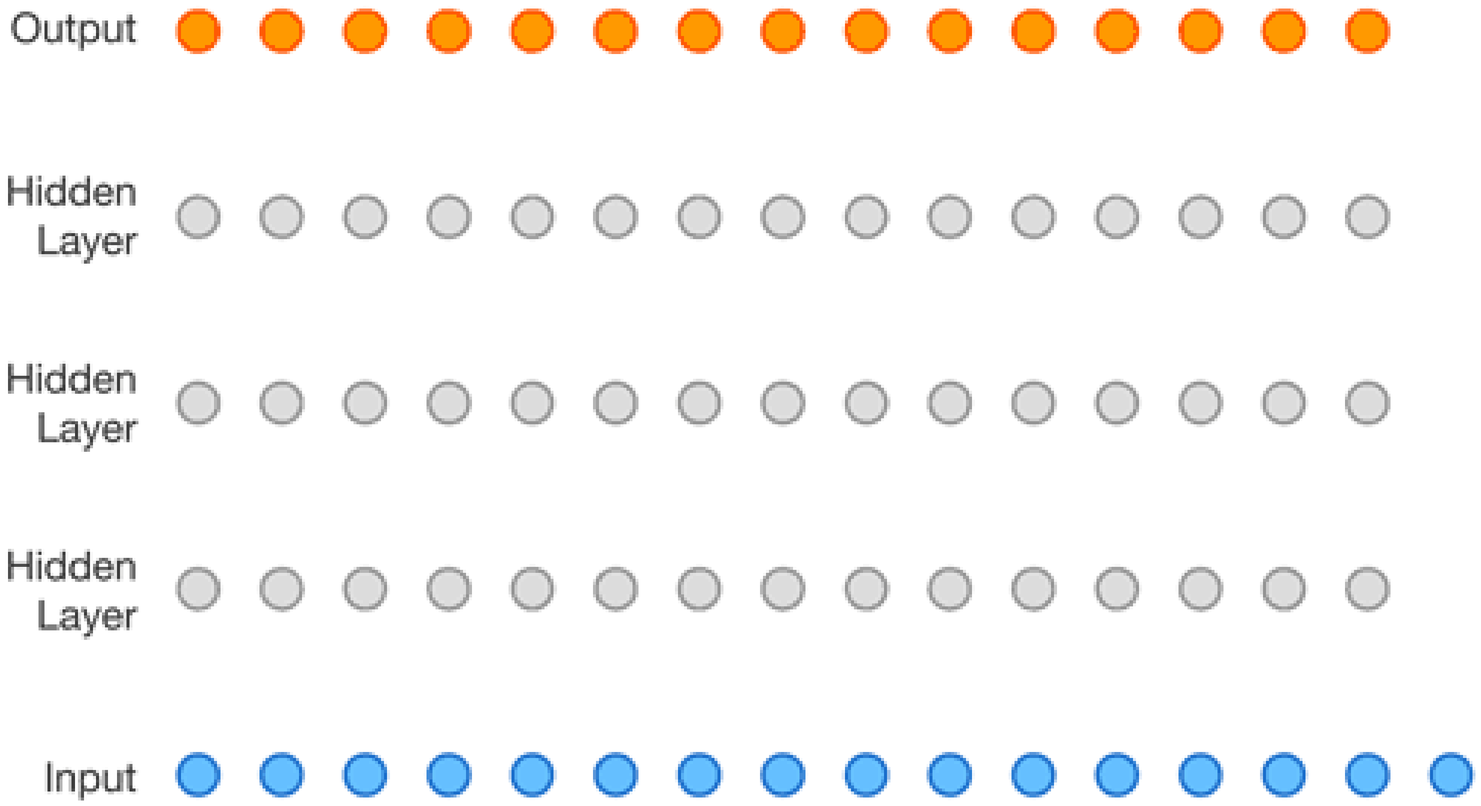


Image source

WaveNet: Results

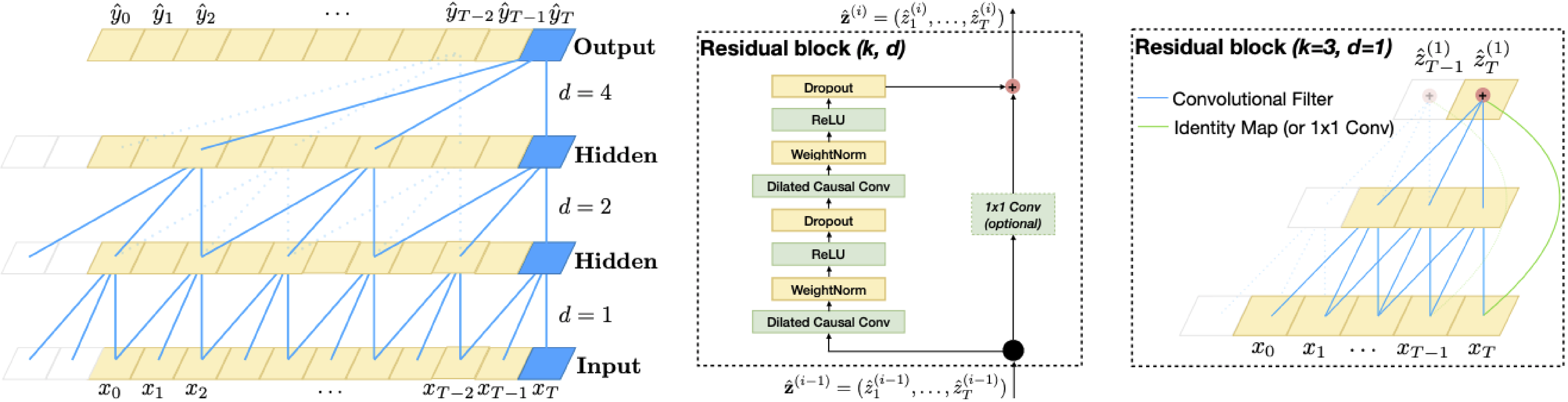
- Text-to-speech with different speaker identities:

- Generated sample of classical piano music:

https://deepmind.com/blog/article/wavenet-generative-model-raw-audio

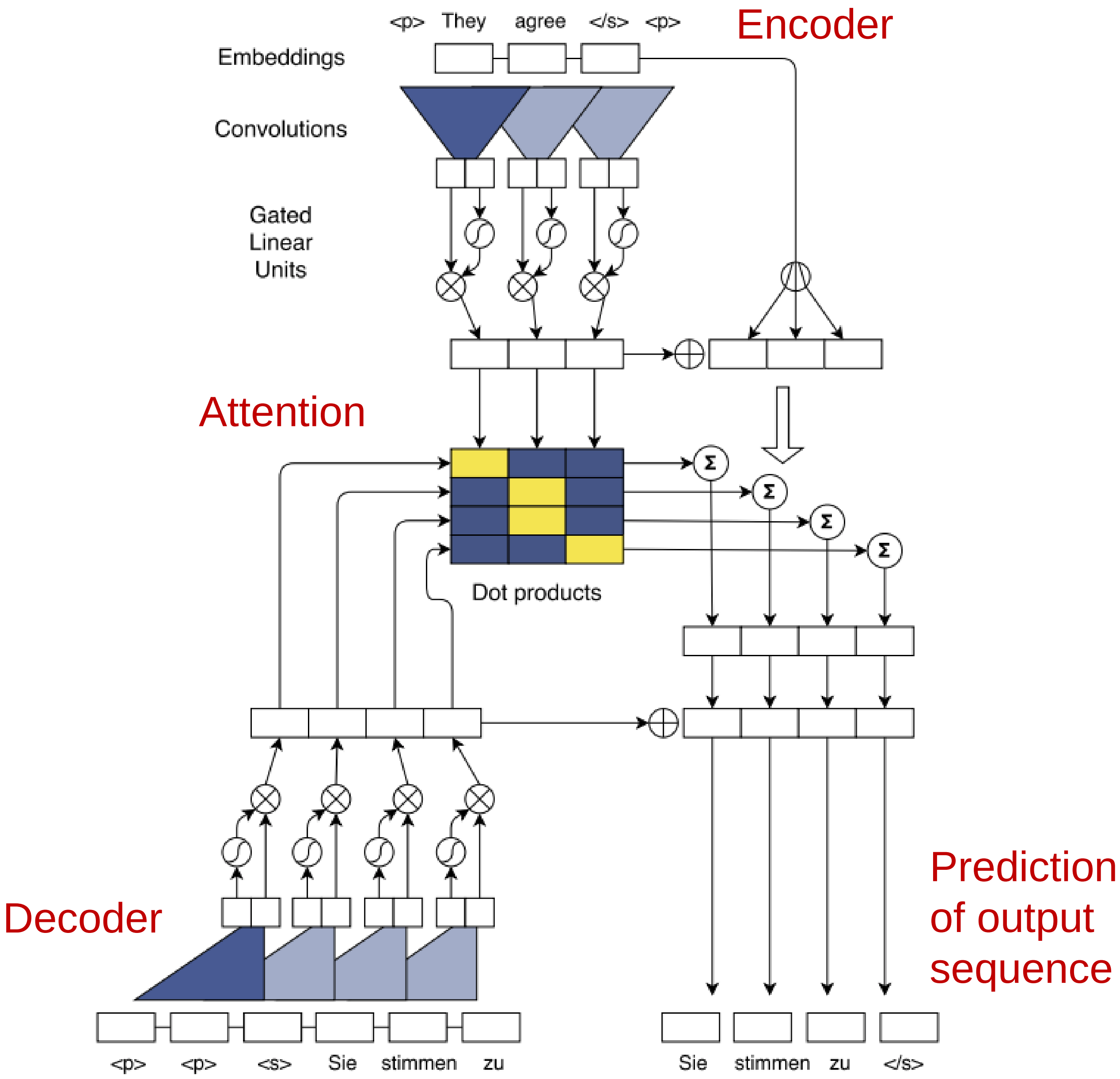
Temporal convolutional networks (TCNs)

- TCNs can be competitive with RNNs for a variety of sequence modeling tasks



S. Bai, J. Kolter, and V. Koltun, [An Empirical Evaluation of Generic Convolutional and Recurrent Networks for Sequence Modeling](), arXiv 2018

Convolutional seq2seq with attention



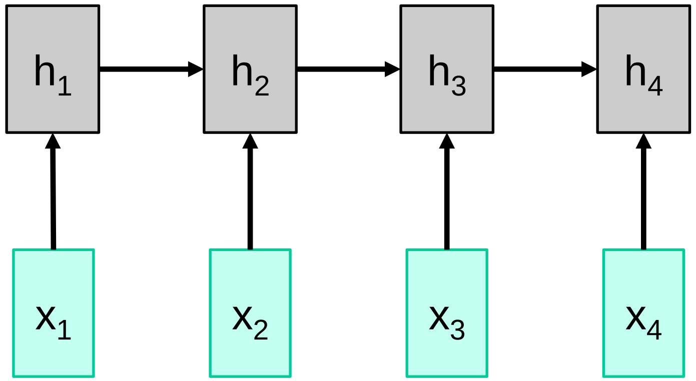
WMT'14 English-German	**BLEU**
Luong et al. (2015) LSTM (Word 50K)	20.9
Kalchbrenner et al. (2016) ByteNet (Char)	23.75
Wu et al. (2016) GNMT (Word 80K)	23.12
Wu et al. (2016) GNMT (Word pieces)	24.61
ConvS2S (BPE 40K)	25.16

WMT'14 English-French	**BLEU**
Wu et al. (2016) GNMT (Word 80K)	37.90
Wu et al. (2016) GNMT (Word pieces)	38.95
Wu et al. (2016) GNMT (Word pieces) + RL	39.92
ConvS2S (BPE 40K)	40.51

J. Gehring, M. Auli, D. Grangier, D. Yarats, Y. Dauphin, [Convolutional sequence to sequence learning](), ICML 2017

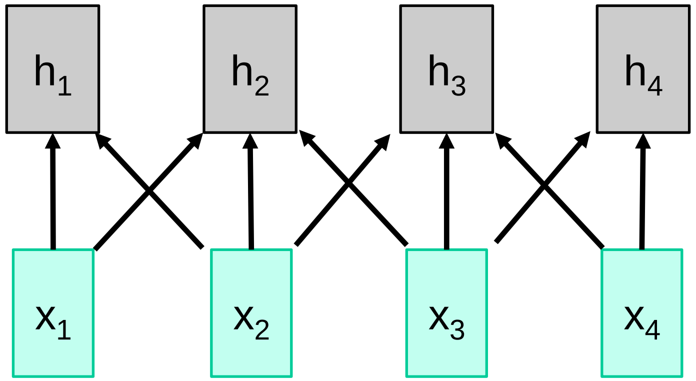
Different ways of processing sequences

RNN



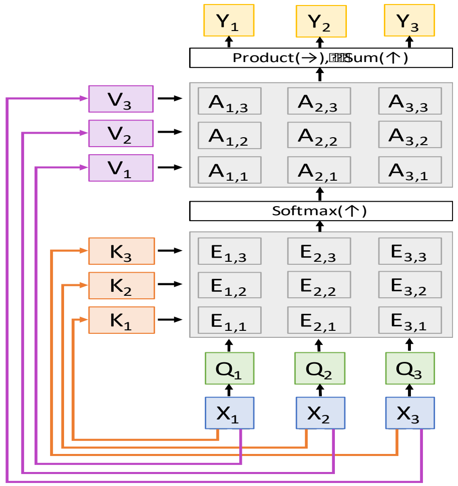
Works on **ordered sequences**
- Pros: Good at long sequences: After one RNN layer, h_T "sees" the whole sequence
- Cons: Not parallelizable: need to compute hidden states sequentially

1D convolutional network



Works on **multidimensional grids**
- Con: Bad at long sequences: Need to stack many conv layers for outputs to "see" the whole sequence
- Pro: Highly parallel: Each output can be computed in parallel

Self-attention and Transformer



- Works on **sets of vectors**
- Pro: Good at long sequences: after one self-attention layer, each output "sees" all inputs!
- Pro: Highly parallel: Each output can be computed in parallel
- Con: Very memory-intensive

Acknowledgement

Thanks to the following courses and corresponding researchers for making their teaching/research material online

- Deep Learning, Stanford University
- Introduction to Deep Learning, University of Illinois at Urbana-Champaign
- Introduction to Deep Learning, Carnegie Mellon University
- Convolutional Neural Networks for Visual Recognition, Stanford University
- Natural Language Processing with Deep Learning, Stanford University
- And Many More ......