Topics:

- Attention and Transformers

CS 4644-DL / 7643-A
ZSOLT KIRA

Lecture Outline

- Machine Translation with RNNs
- RNNs with Attention
- From Attention to Transformers
- What can Transformers do?

Slides from Justin Johnson, modified by Arjun Madjumdar

Sequence Modeling with RNNs

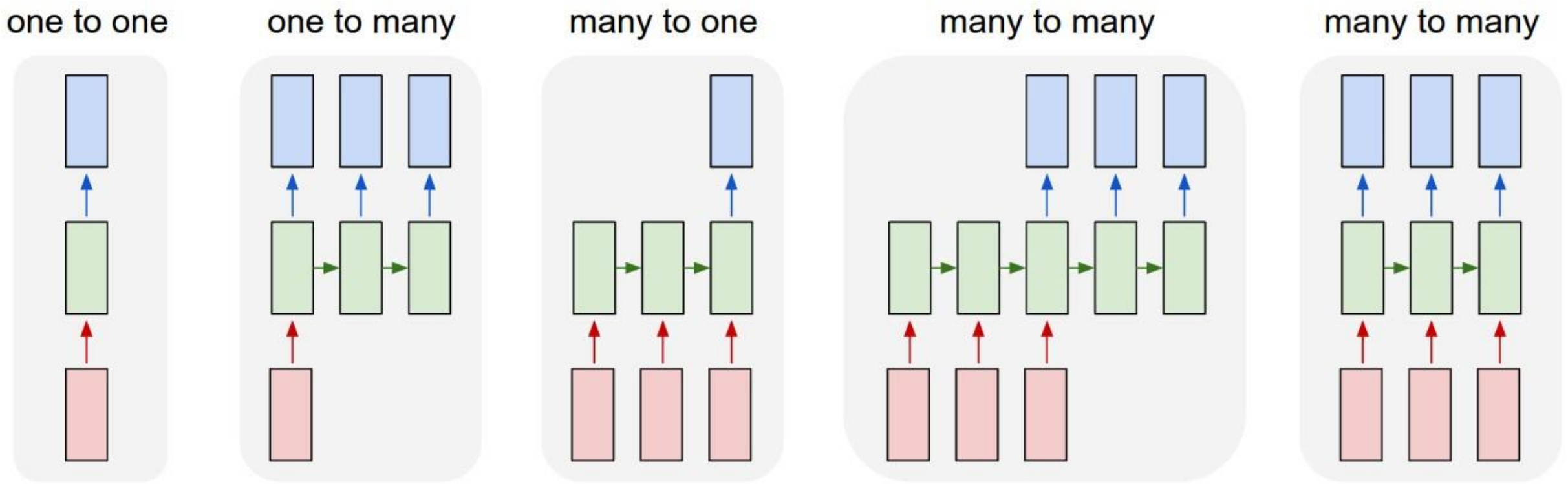
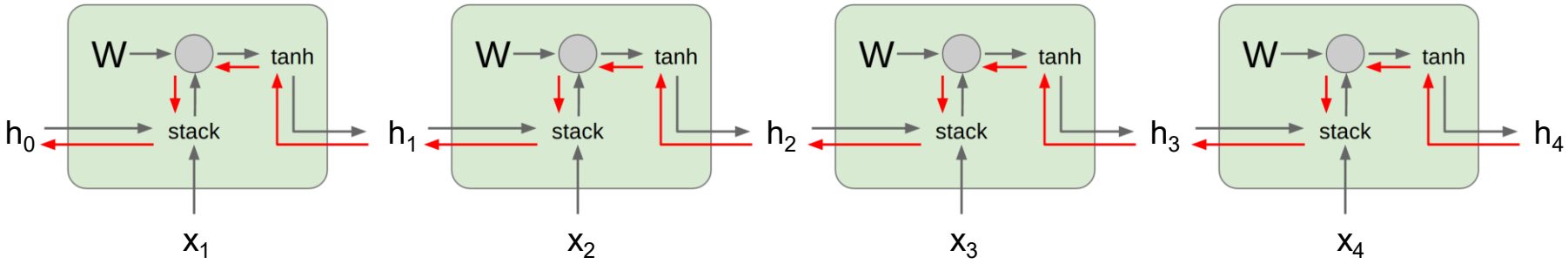


Image Credit: Andrej Karpathy

Vanilla RNN Gradient Flow

Bengio et al, “Learning long-term dependencies with gradient descent is difficult”, IEEE Transactions on Neural Networks, 1994
Pascanu et al, “On the difficulty of training recurrent neural networks”, ICML 2013



$$
\begin{aligned}
h_t &= \tanh(W_{hh}h_{t-1} + W_{xh}x_t) \\
&= \tanh\left(\begin{pmatrix} W_{hh} & W_{hx} \end{pmatrix} \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix} \right) \\
&= \tanh\left(W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix} \right)
\end{aligned}
$$

How can we train this on language?

- Supervised Learning:
  - Sentiment analysis (sentence -> negative/neutral/positive) labeled by humans
  - Translation -> English and equivalent other language

- Self-supervised: Predict the next letter or word!
  - This is **extremely powerful!!**
  - In order to predict what's next, it needs to really understand not just language statistics but world knowledge!
    - Of course, we need scale for this level of loss reduction / understanding

- **Training:** A large corpus of text from the web
  - Note: No annotation required! It's just "the text"

- **Inference:** Just generate me new text
  - Can condition on some initial input (**prompt**)

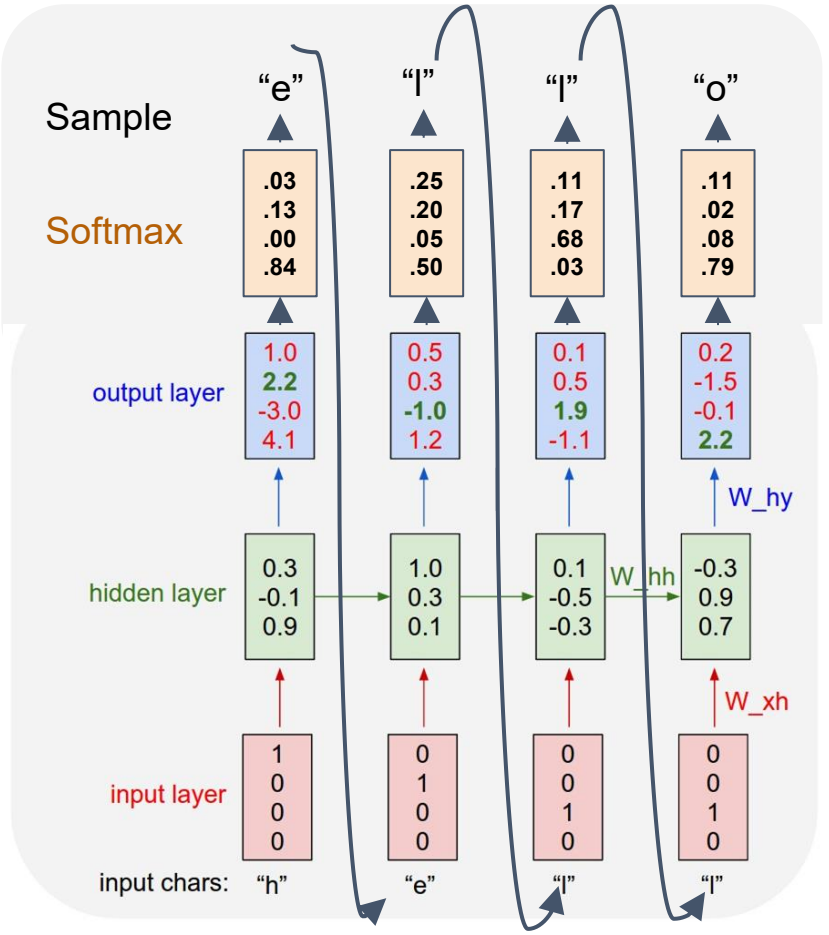
```
#include <asm/io.h>
#include <asm/prom.h>
#include <asm/e820.h>
#include <asm/system_info.h>
#include <asm/setew.h>
#include <asm/pgproto.h>

#define REG_PG    vesa_slot_addr_pack
#define PFM_NOCOMP  AFSR(0, load)
#define STACK_DDR(type)     (func)

#define SWAP_ALLOCATE(nr)     (e)
#define emulate_sigs()  arch_get_unaligned_child()
#define access_rw(TST)  asm volatile("movd %%esp, %0, %3" : : "r" (0));   \
  if (__type & DO_READ)

static void stat_PC_SEC __read_mostly offsetof(struct seq_argsqueue, \
          pC>[1]);

static void
os_prefix(unsigned long sys)
{
#ifdef CONFIG_PREEMPT
  PUT_PARAM_RAID(2, sel) = get_state_state();
  set_pid_sum((unsigned long)state, current_state_str(),
           (unsigned long)-1->lr_full; low;
}
```

Test Time: Sample / Argmax / Beam Search

Example: Character-level Language Model Sampling

Vocabulary:
[h,e,l,o]

At test-time sample characters one at a time, feed back to model



Can also feed in predictions during training (student forcing)

Long Short Term Memory (LSTM)

Vanilla RNN

$$h_t = \tanh\left(W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}\right)$$

LSTM

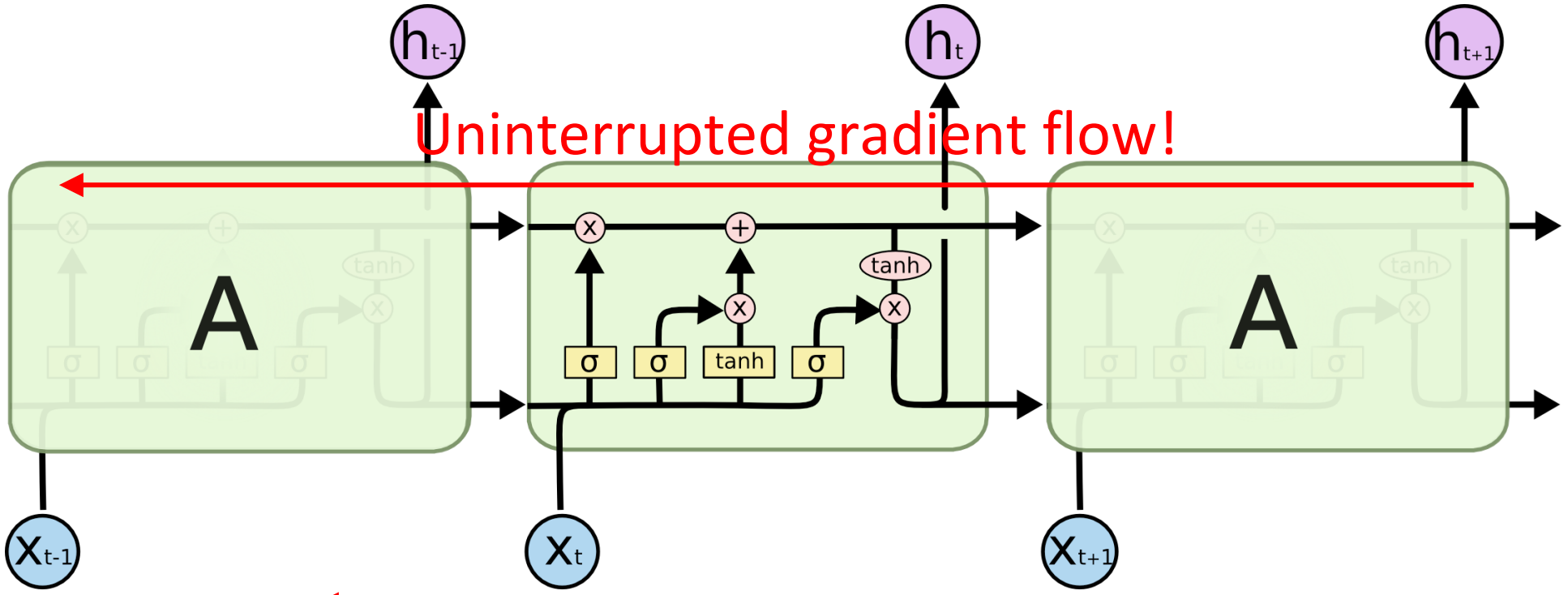
$$\begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}$$

$$c_t = f \odot c_{t-1} + i \odot g$$

$$h_t = o \odot \tanh(c_t)$$

Hochreiter and Schmidhuber, "Long Short Term Memory", Neural Computation 1997

LSTMs Intuition: Additive Updates



Similar to ResNet!

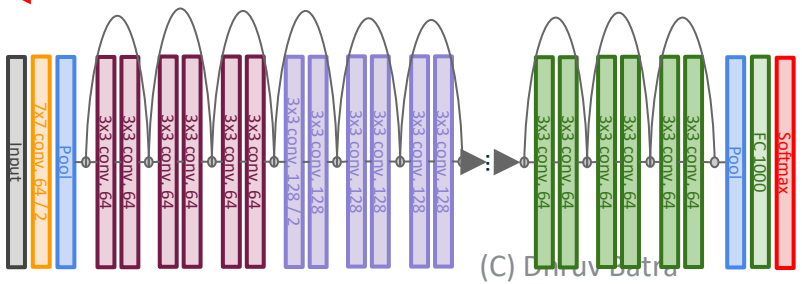


Image Credit: Christopher Olah (http://colah.github.io/posts/2015-08-Understanding-LSTMs/)

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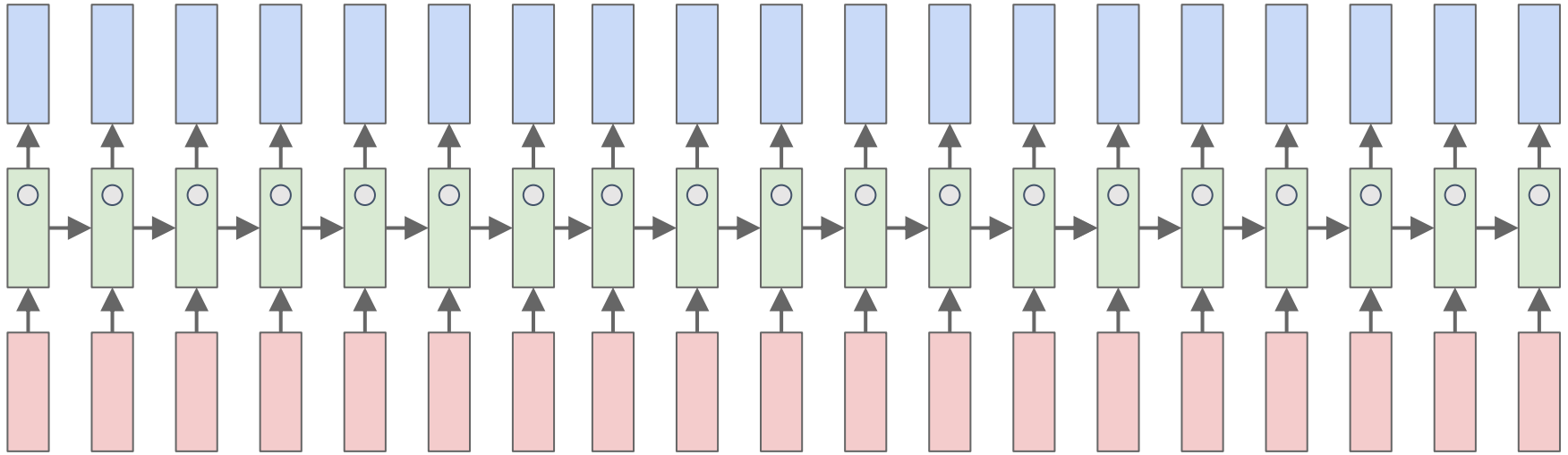
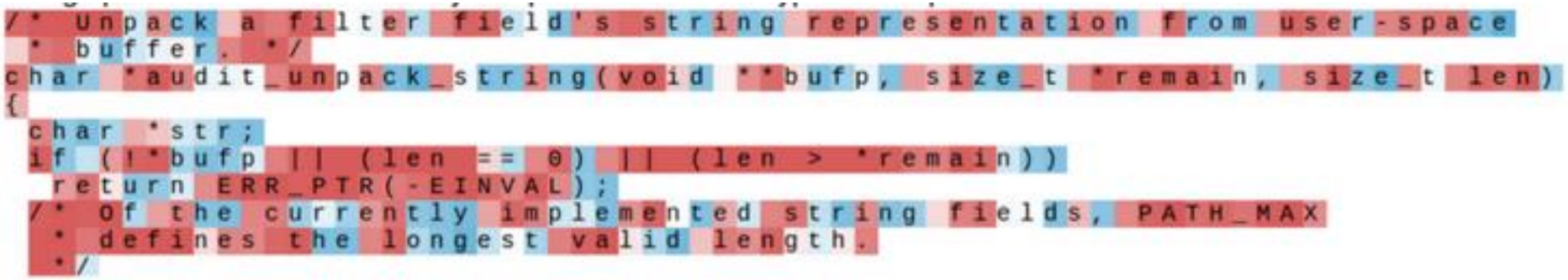
Slide Credit: Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

Searching for interpretable cells



Karpathy, Johnson, and Fei-Fei: Visualizing and Understanding Recurrent Networks, ICLR Workshop 2016

Searching for interpretable cells



```
/* Unpack a filter field's string representation from user-space
 * buffer. */
char *audit_unpack_string(void **bufp, size_t *remain, size_t len)
{
  char *str;
  if (!*bufp || (len == 0) || (len > *remain))
    return ERR_PTR(-EINVAL);
  /* Of the currently implemented string fields, PATH_MAX
   * defines the longest valid length.
   */
```

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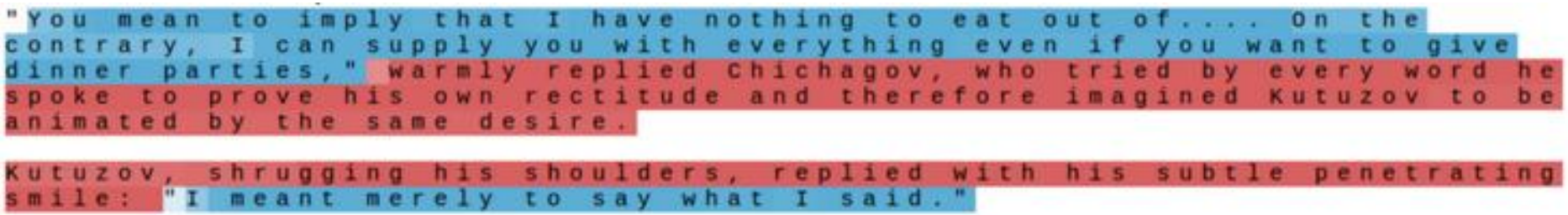
Searching for interpretable cells



quote detection cell

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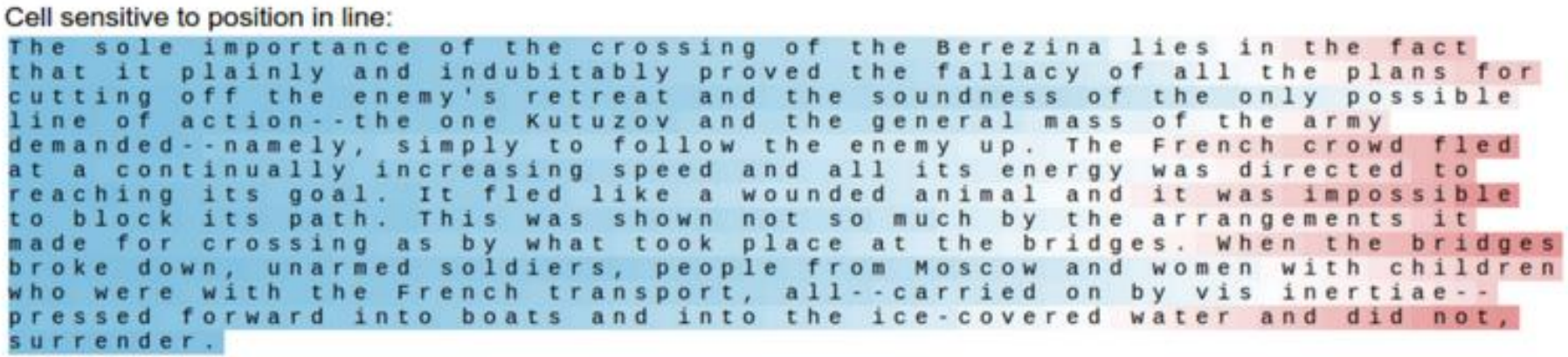

line length tracking cell

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Searching for interpretable cells

```
static int __dequeue_signal(struct sigpending *pending, sigset_t *mask,
        siginfo_t *info)
{
  int sig = next_signal(pending, mask);
  if (sig) {
    if (current->notifier) {
      if (sigismember(current->notifier_mask, sig)) {
        if (!(current->notifier)(current->notifier_data)) {
          clear_thread_flag(TIF_SIGPENDING);
          return 0;
        }
      }
    }
    collect_signal(sig, pending, info);
  }
  return sig;
}
```

if statement cell

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Searching for interpretable cells

Cell that turns on inside comments and quotes:

```
/* Duplicate LSM field information.  The lsm_rule is opaque, so
 * re-initialized. */
static inline int audit_dupe_lsm_field(struct audit_field *df,
                                       struct audit_field *sf)
{
  int ret = 0;
  char *lsm_str;
  /* our own copy of lsm_str */
  lsm_str = kstrdup(sf->lsm_str, GFP_KERNEL);
  if (unlikely(!lsm_str))
    return -ENOMEM;
  df->lsm_str = lsm_str;
  /* our own (refreshed) copy of lsm_rule */
  ret = security_audit_rule_init(df->type, df->op, df->lsm_str,
                                 (void **)&df->lsm_rule);
  /* Keep currently invalid fields around in case they
   * become valid after a policy reload. */
  if (ret == -EINVAL) {
    pr_warn("audit rule for LSM \'%s\' is invalid\n",
            df->lsm_str);
    ret = 0;
  }
  return ret;
}
```

quote/comment cell

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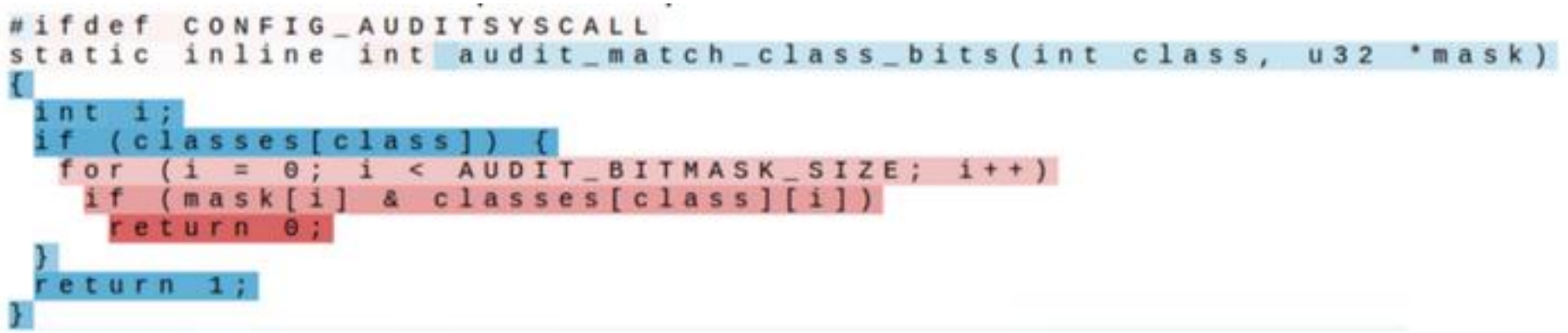
Searching for interpretable cells



```
#ifdef CONFIG_AUDITSYSCALL
static inline int audit_match_class_bits(int class, u32 *mask)
{
  int i;
  if (classes[class]) {
    for (i = 0; i < AUDIT_BITMASK_SIZE; i++)
      if (mask[i] & classes[class][i])
        return 0;
  }
  return 1;
}
```

code depth cell

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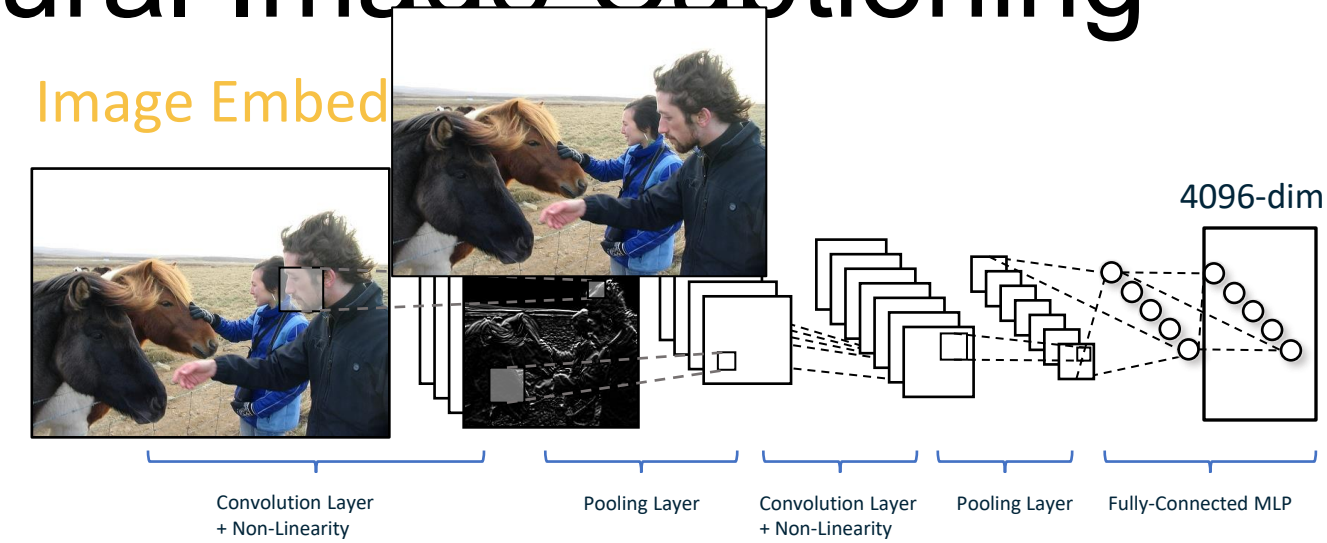
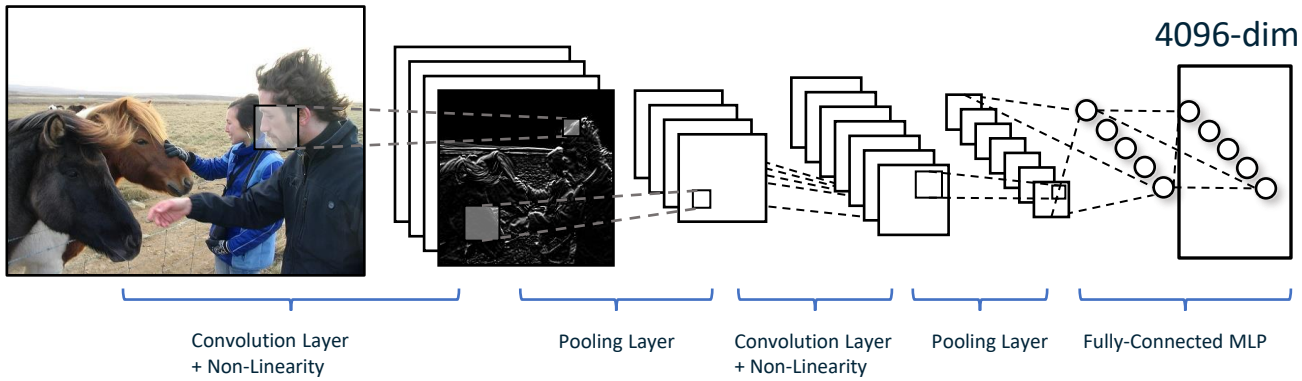
Neural Image Captioning

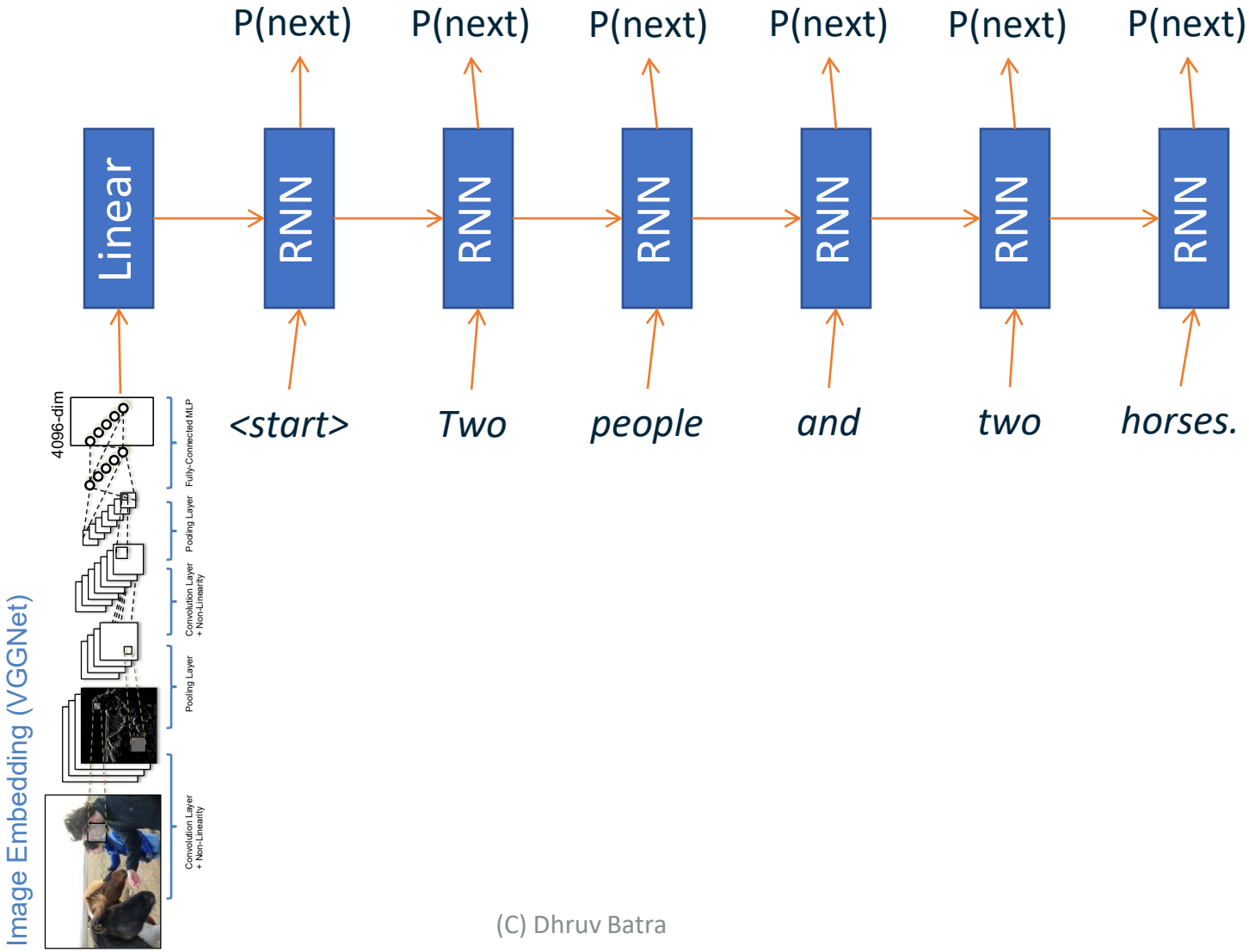


Neural Image Captioning

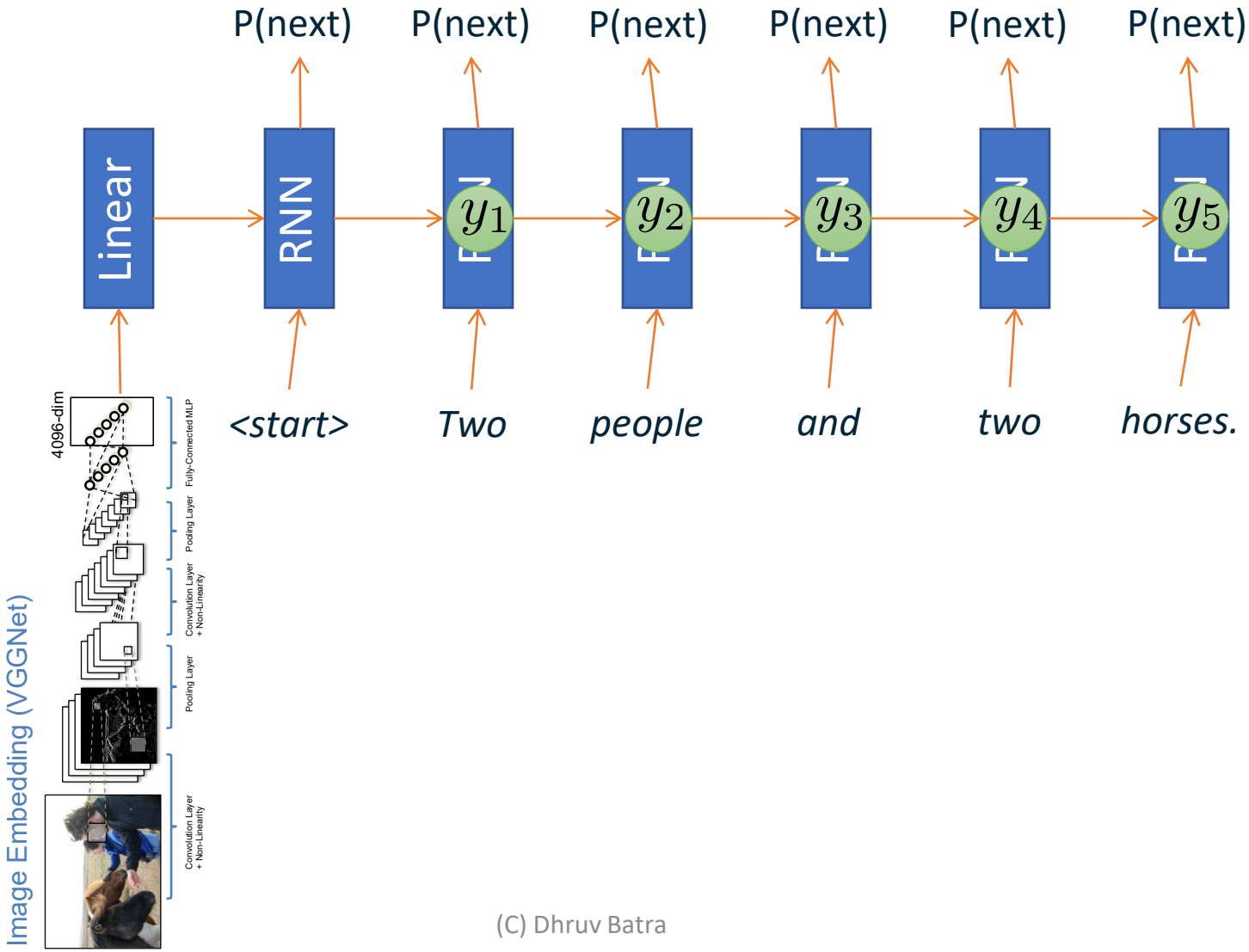
Image Embedding (VGGNet)



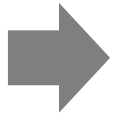
Neural Image Captioning



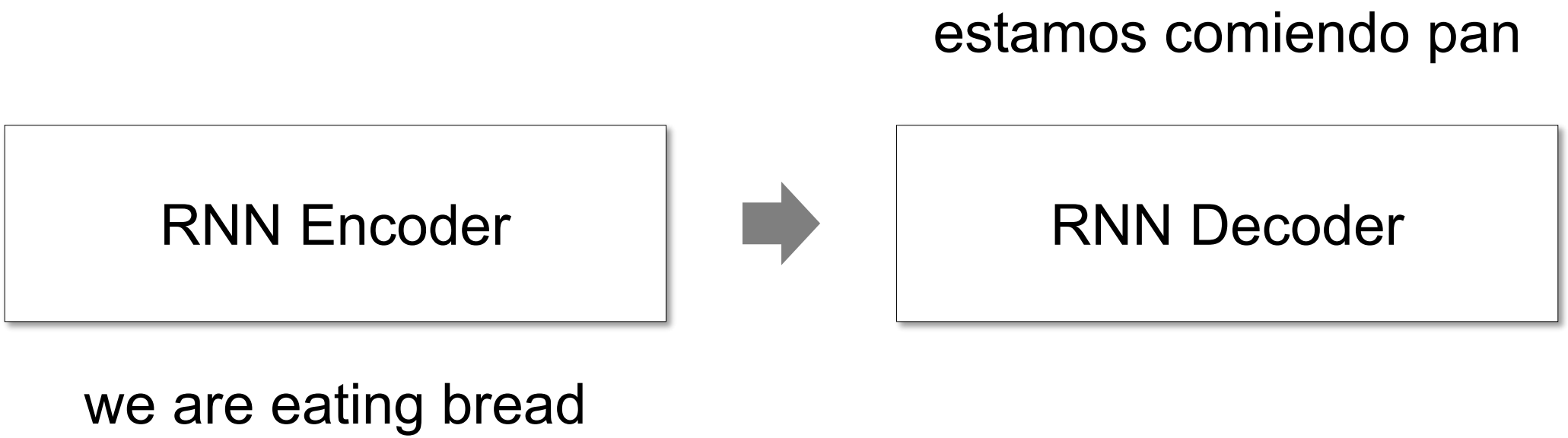
Neural Image Captioning



Machine Translation

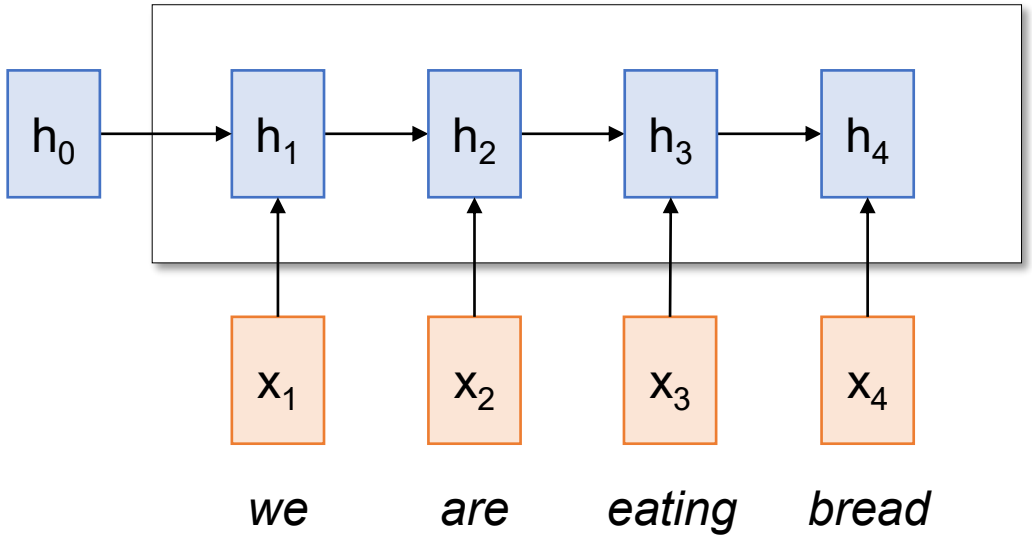
we are eating bread  estamos comiendo pan

Machine Translation



Machine Translation with RNNs

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

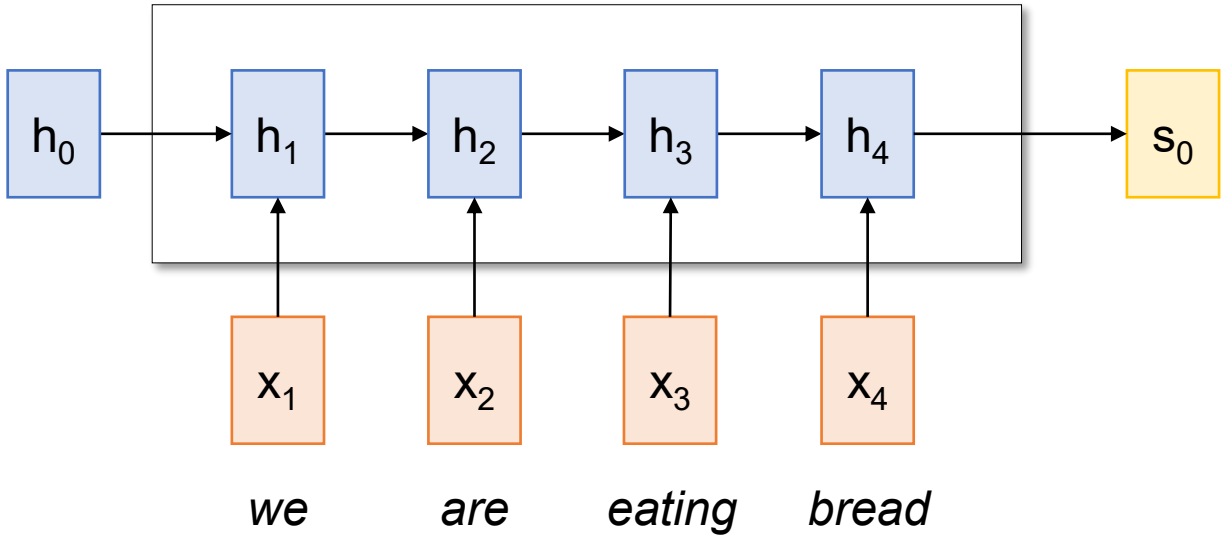


Slide credit: Justin Johnson

Machine Translation with RNNs

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

$s_0 = h_4$

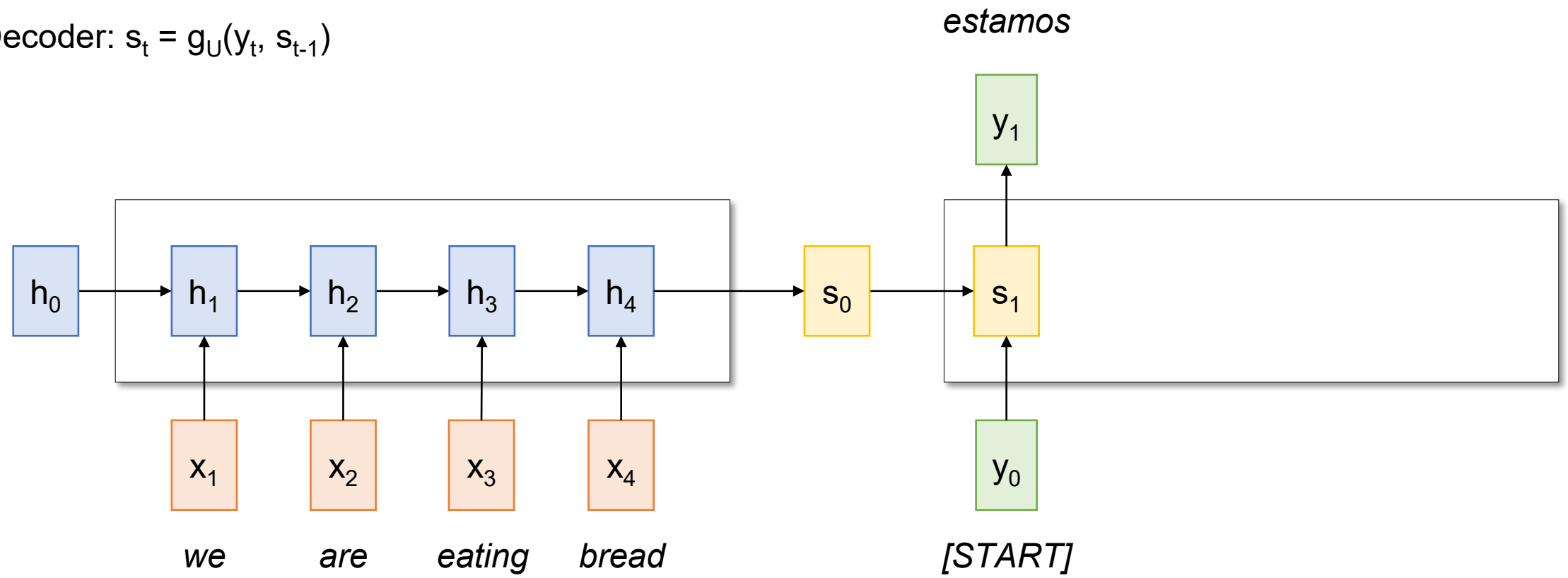


Slide credit: Justin Johnson

Machine Translation with RNNs

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

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



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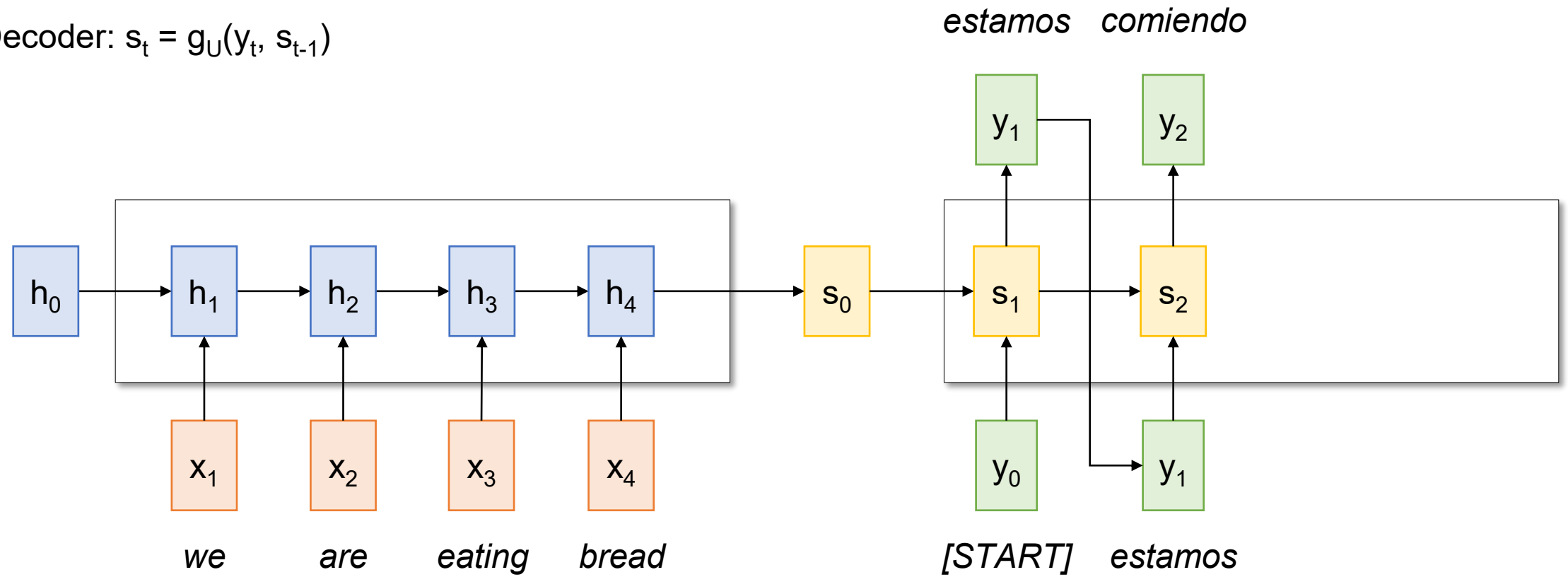

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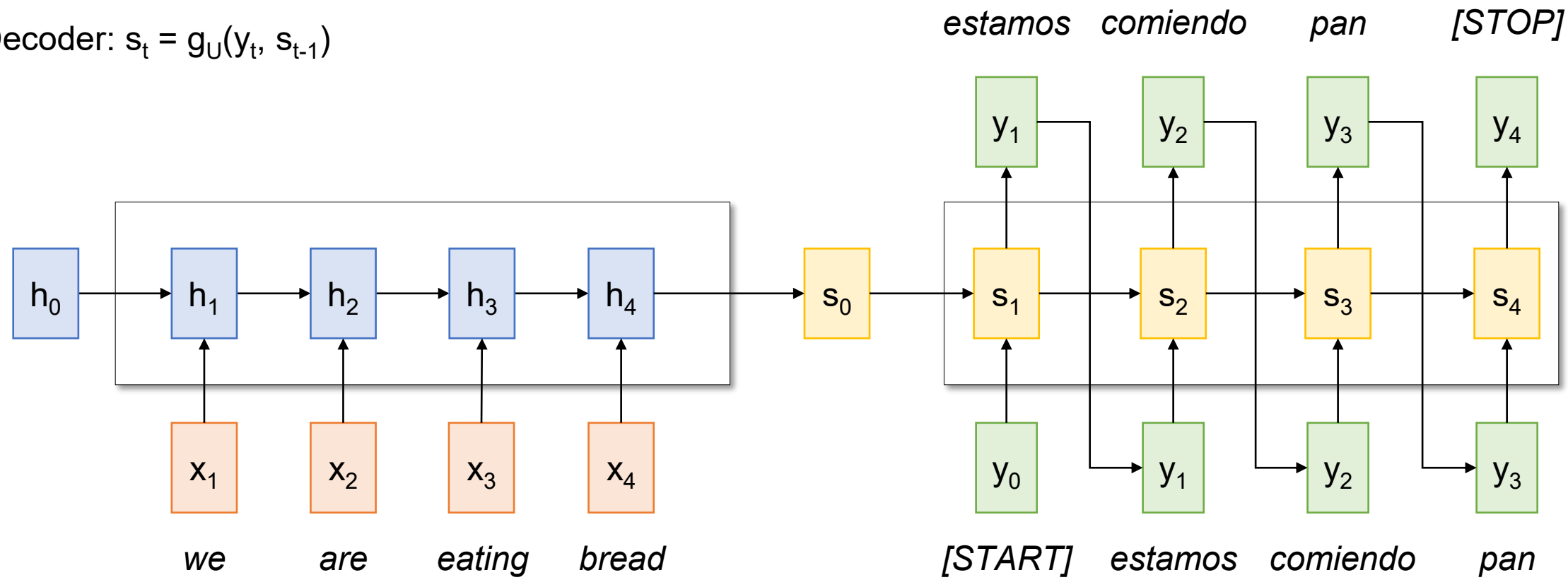
Machine Translation with RNNs

Note [START]/[STOP] words. This can be treated as representation for entire sentence

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

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



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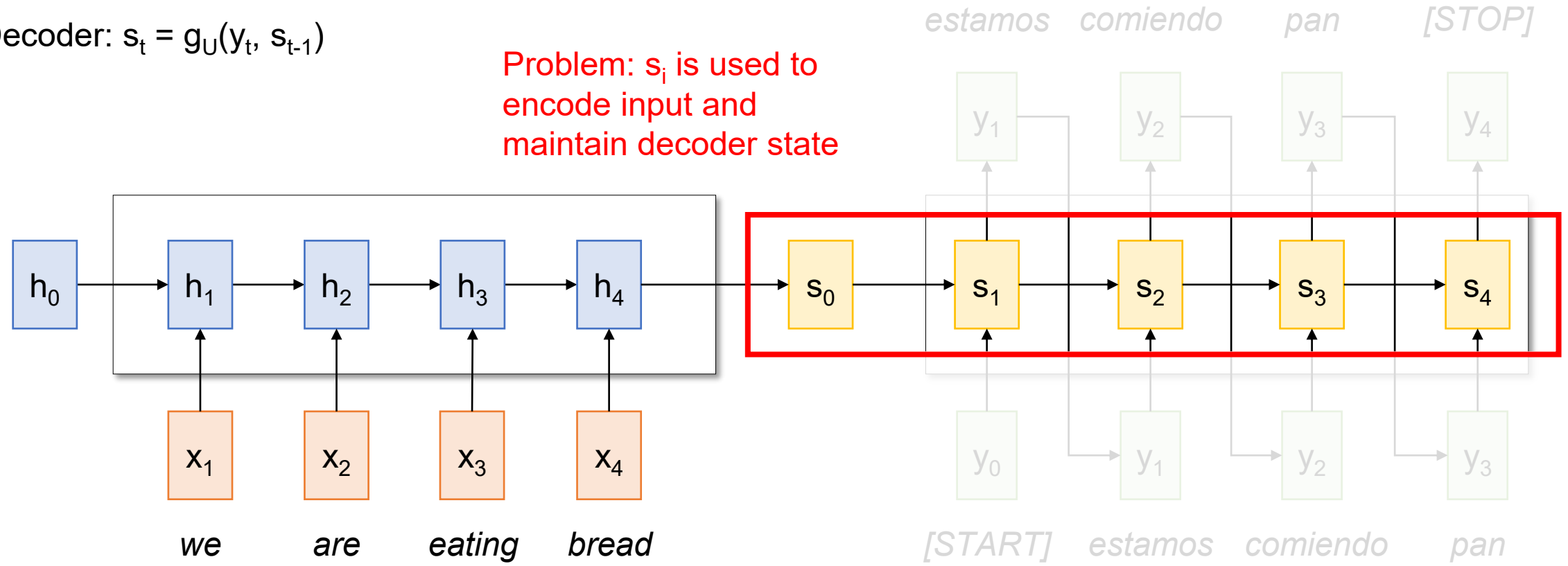
Machine Translation with RNNs

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

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

Problem: s_i is used to encode input and maintain decoder state



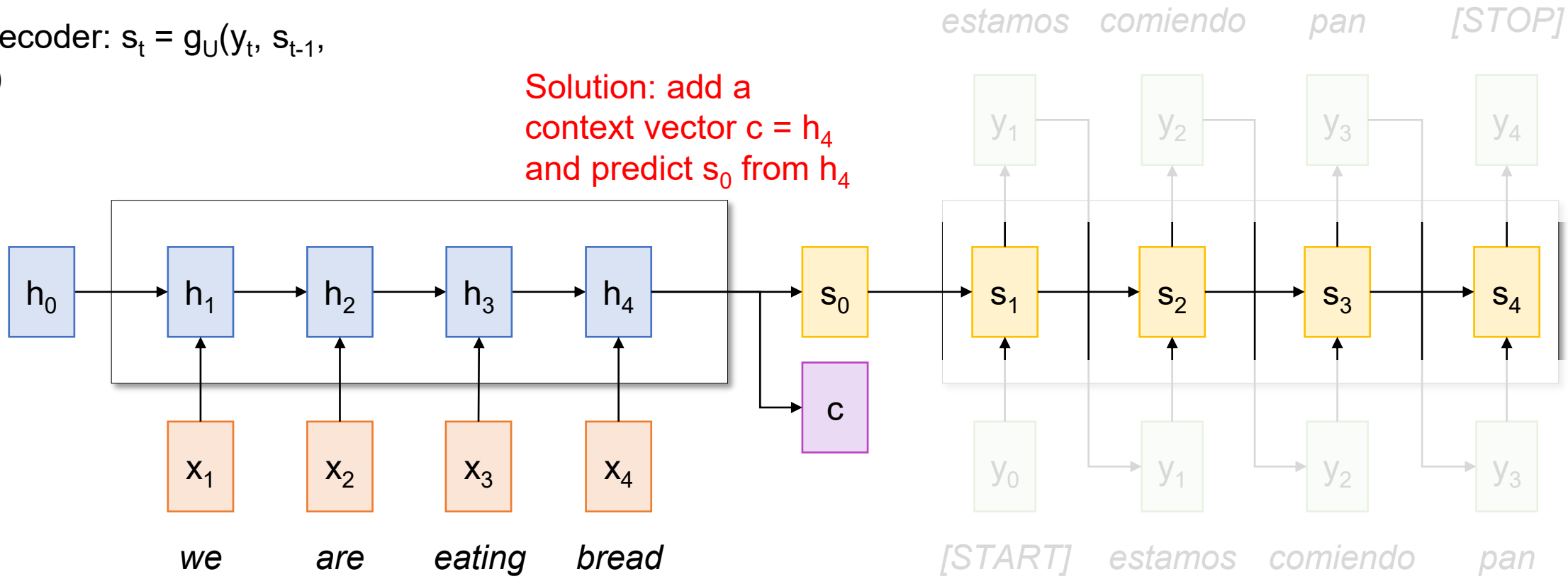
Slide credit: Justin Johnson

Machine Translation with RNNs

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

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

Solution: add a context vector $c = h_4$ and predict s_0 from h_4



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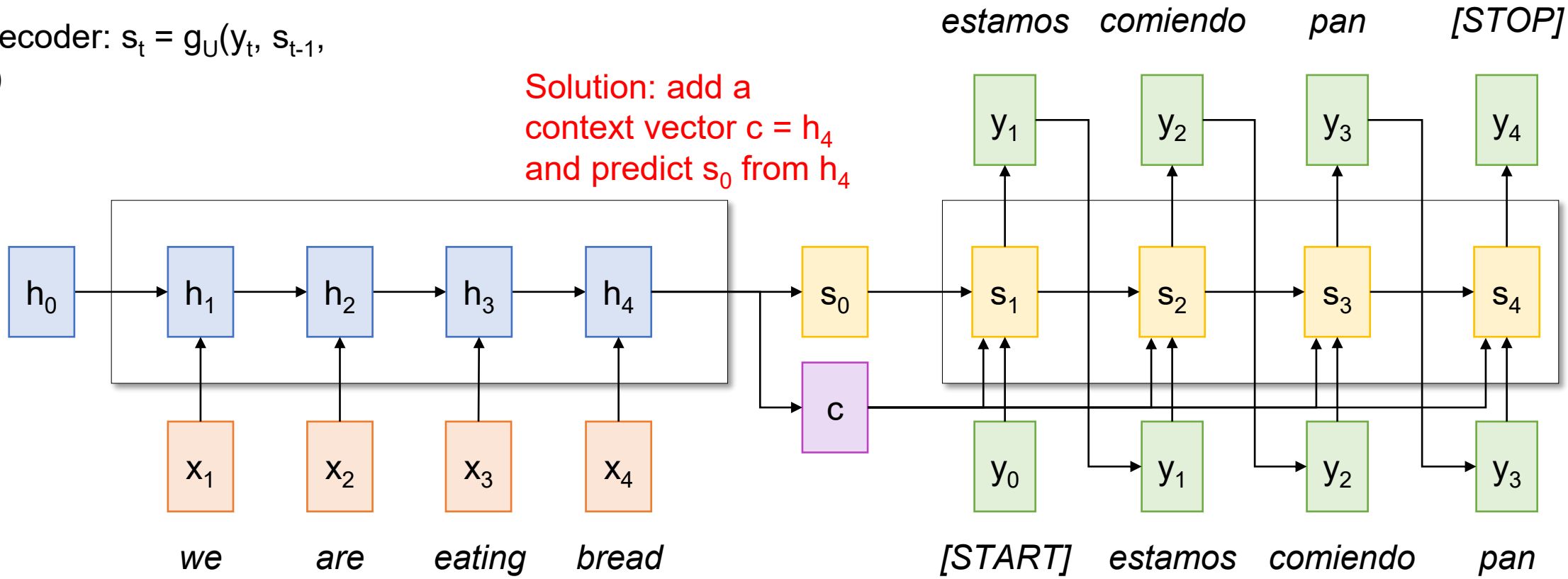

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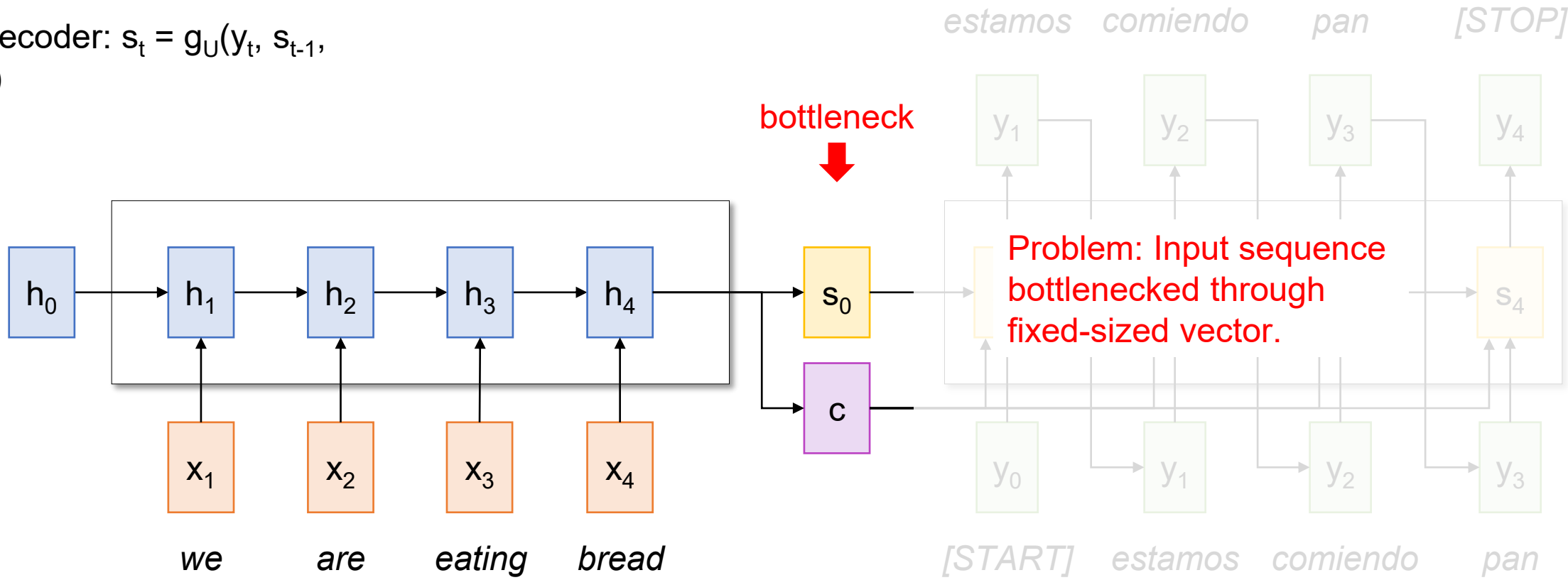

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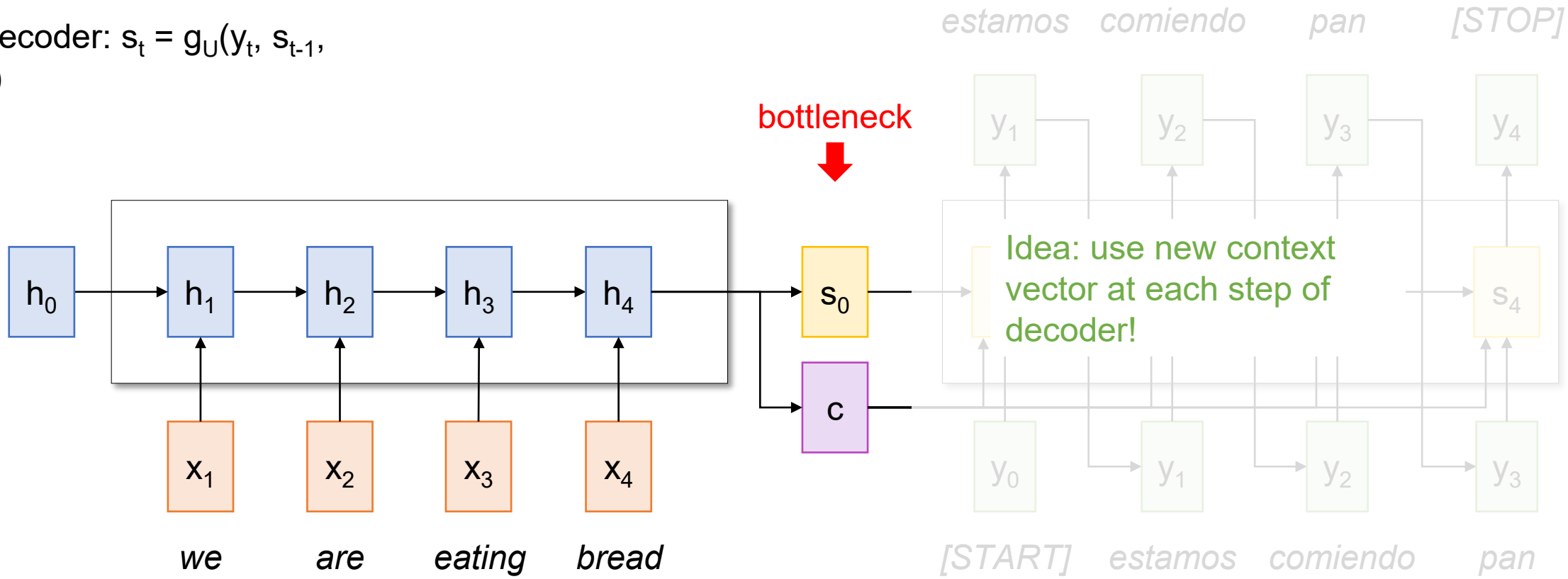
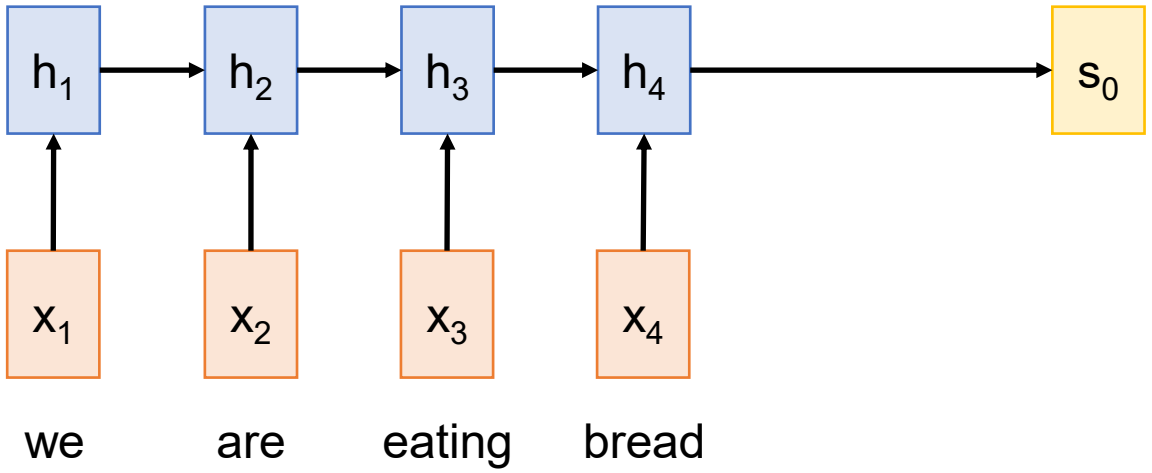


Slide credit: Justin Johnson

Machine Translation with RNNs **and Attention**

From final hidden state:
Initial decoder state s_0



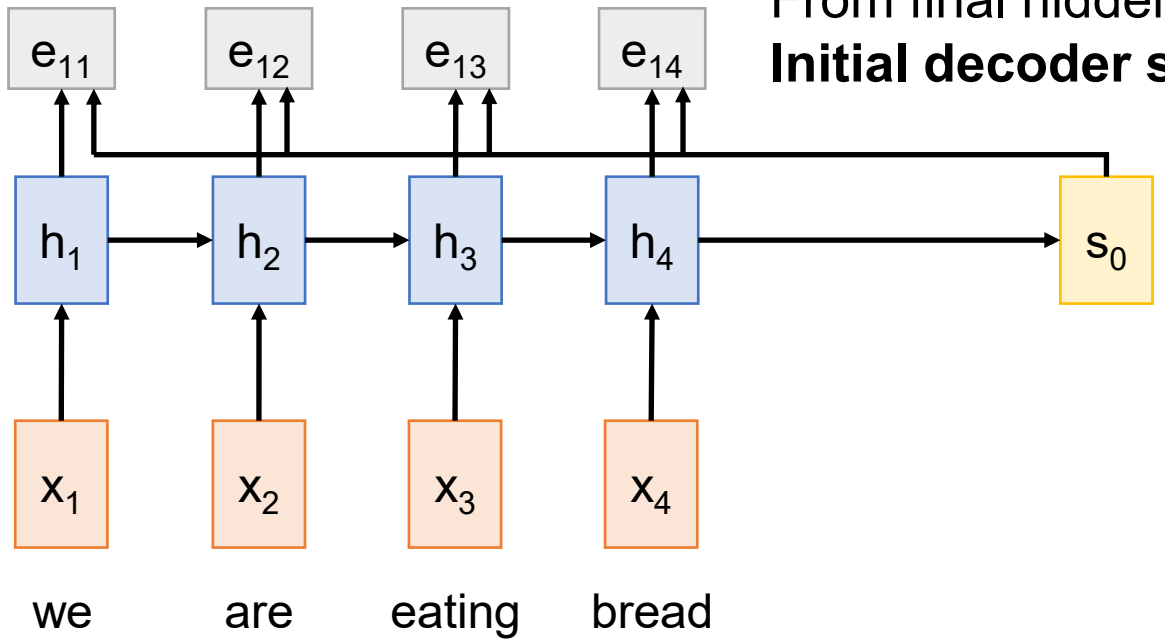
Bahdanau et al, “Neural machine translation by jointly learning to align and translate”, ICLR 2015

Slide credit: Justin Johnson

Machine Translation with RNNs **and Attention**

Compute **alignment scores**

$e_{t,i} = f_{att}(s_{t-1}, h_i)$ **(f_{att} is an MLP)**



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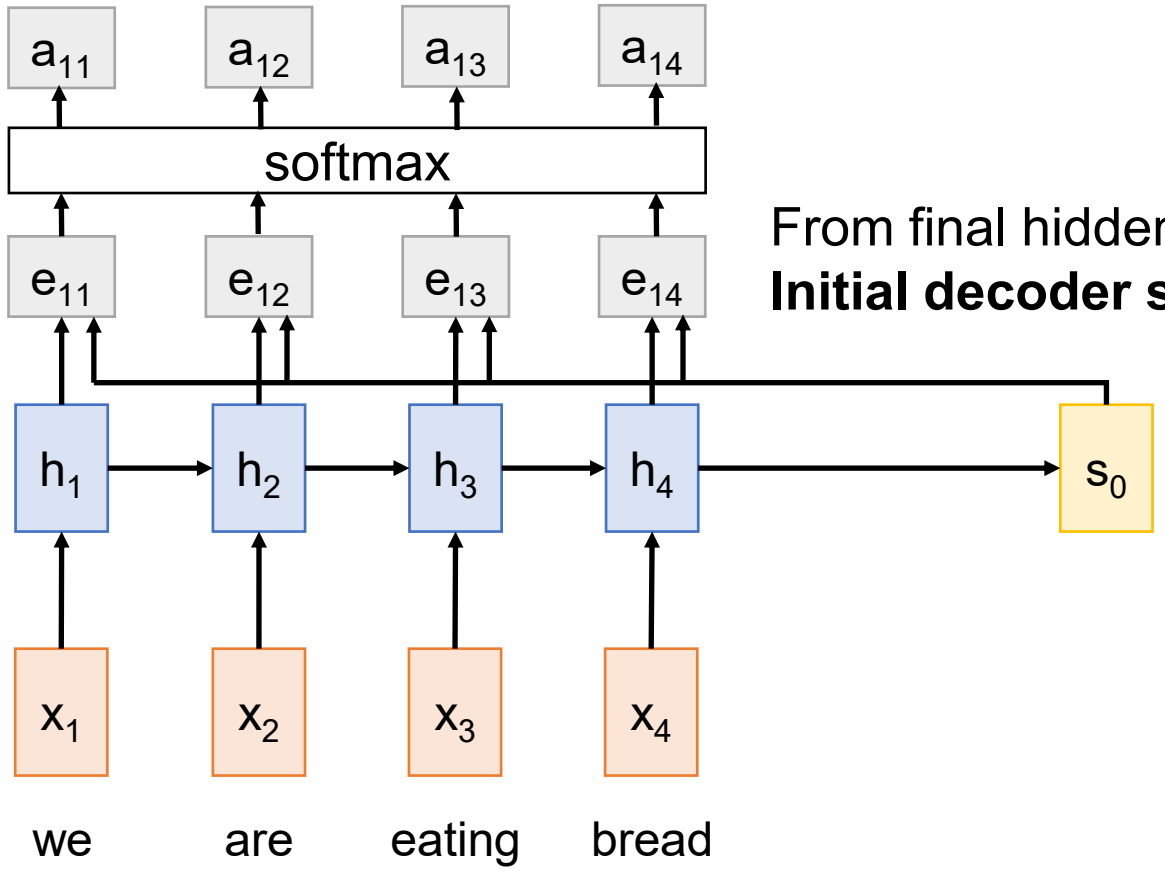

From final hidden state:
Initial decoder state s_0

Compute **alignment scores**

$e_{t,i} = f_{att}(s_{t-1}, h_i)$ **(f_{att} is an MLP)**

Normalize to get **attention weights**

$0 < a_{t,i} < 1 \quad \sum_i a_{t,i} = 1$

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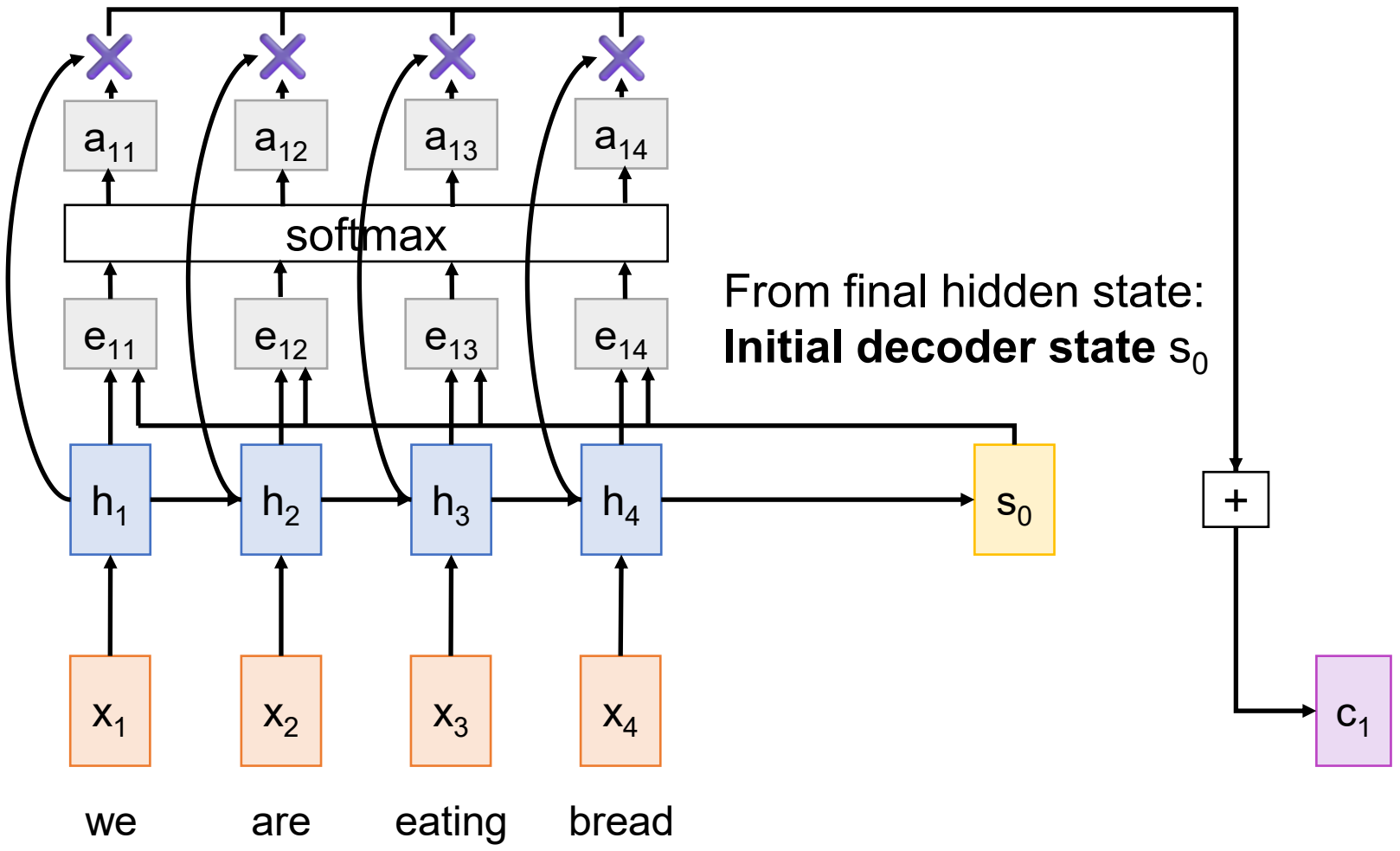
Machine Translation with RNNs **and Attention**



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$0 < a_{t,i} < 1 \quad \sum_i a_{t,i} = 1$

Set context vector **c** to a linear combination of hidden states

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

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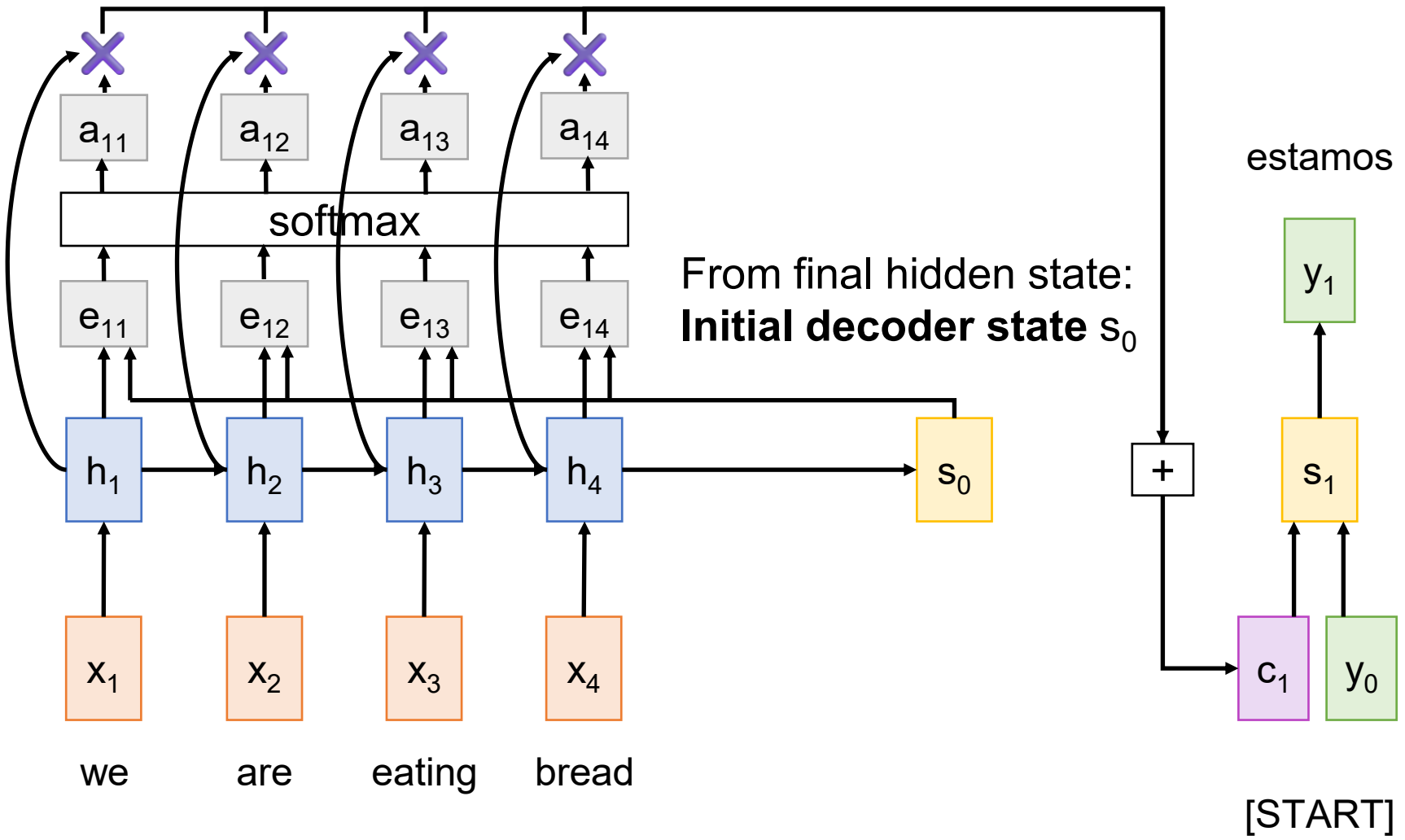
Slide credit: Justin Johnson

Machine Translation with RNNs **and Attention**



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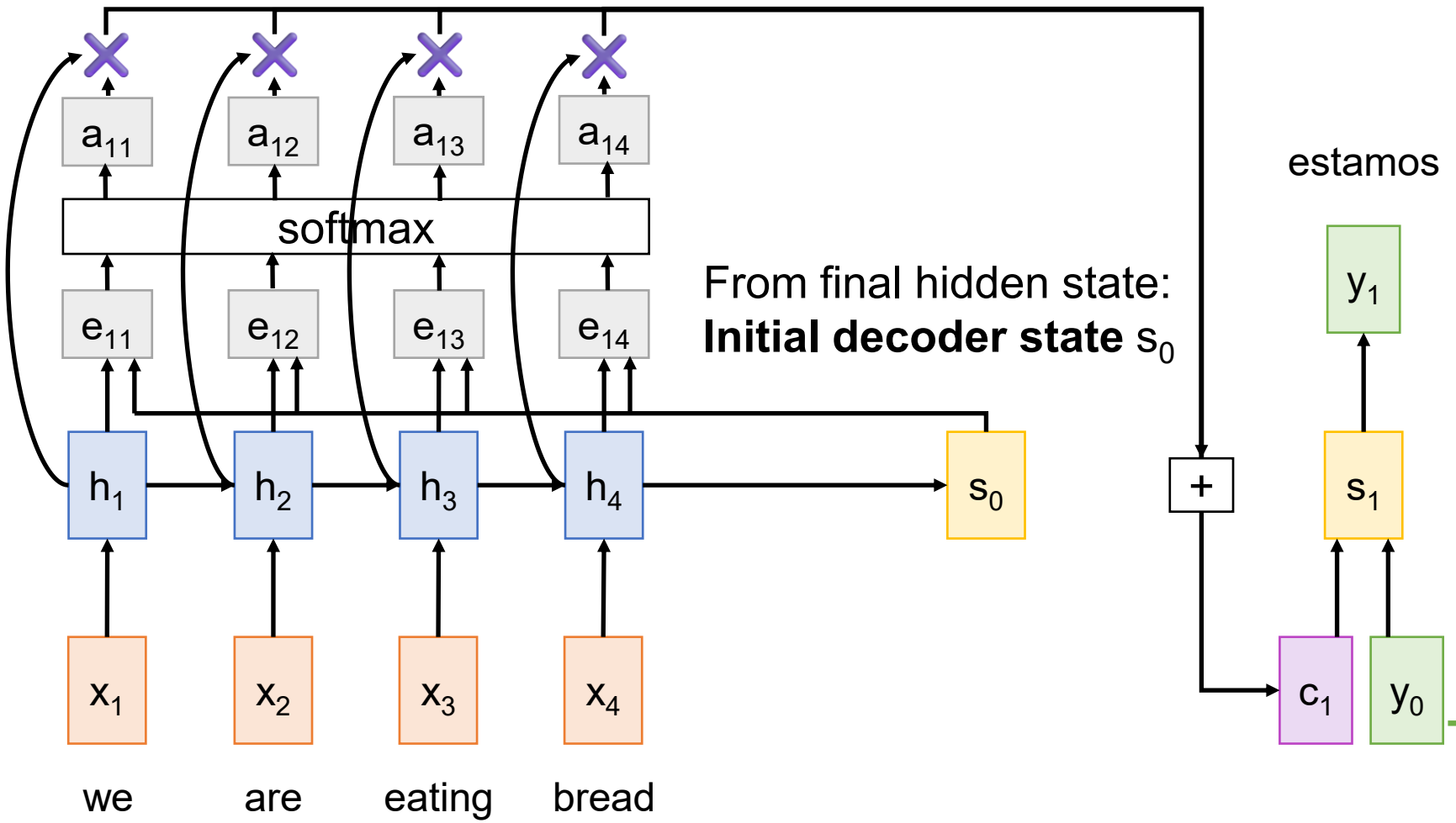

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Set context vector **c** to a linear combination of hidden states

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

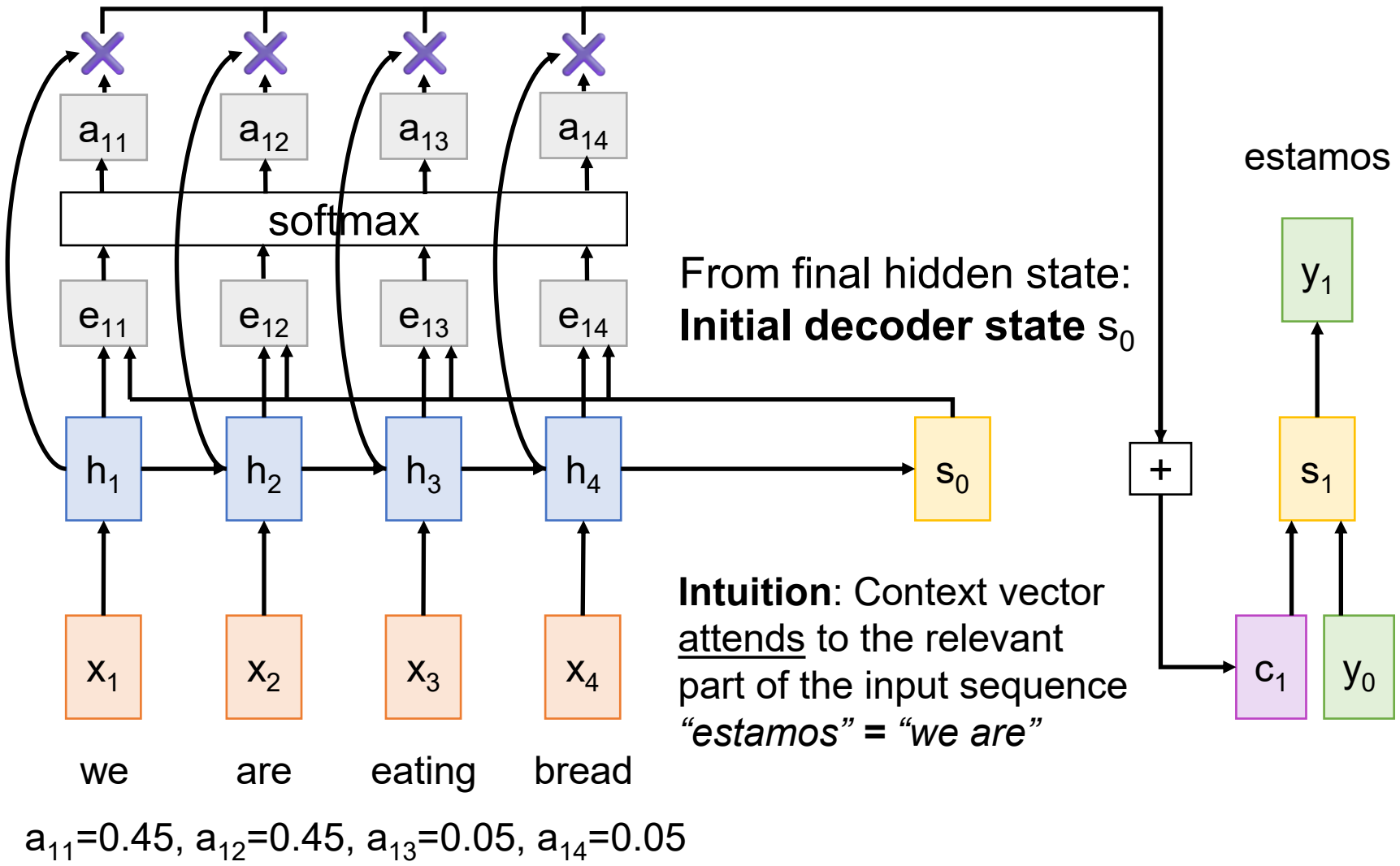
This is all differentiable! Do not supervise attention weights – backprop through everything

Can be seen as a input-dependent weighting (rather than MLP)

Bahdanau et al, "Neural machine translation by jointly learning to align and translate", ICLR 2015

Slide credit: Justin Johnson

Machine Translation with RNNs **and Attention**



From final hidden state:
Initial decoder state s_0

Intuition: Context vector attends to the relevant part of the input sequence
"estamos" **=** *"we are"*

a_{11}=0.45, a_{12}=0.45, a_{13}=0.05, a_{14}=0.05

Compute **alignment scores**
$e_{t,i} = f_{att}(s_{t-1}, h_i)$ **(f_{att} is an MLP)**

Normalize to get **attention weights**
$0 < a_{t,i} < 1 \quad \sum_i a_{t,i} = 1$

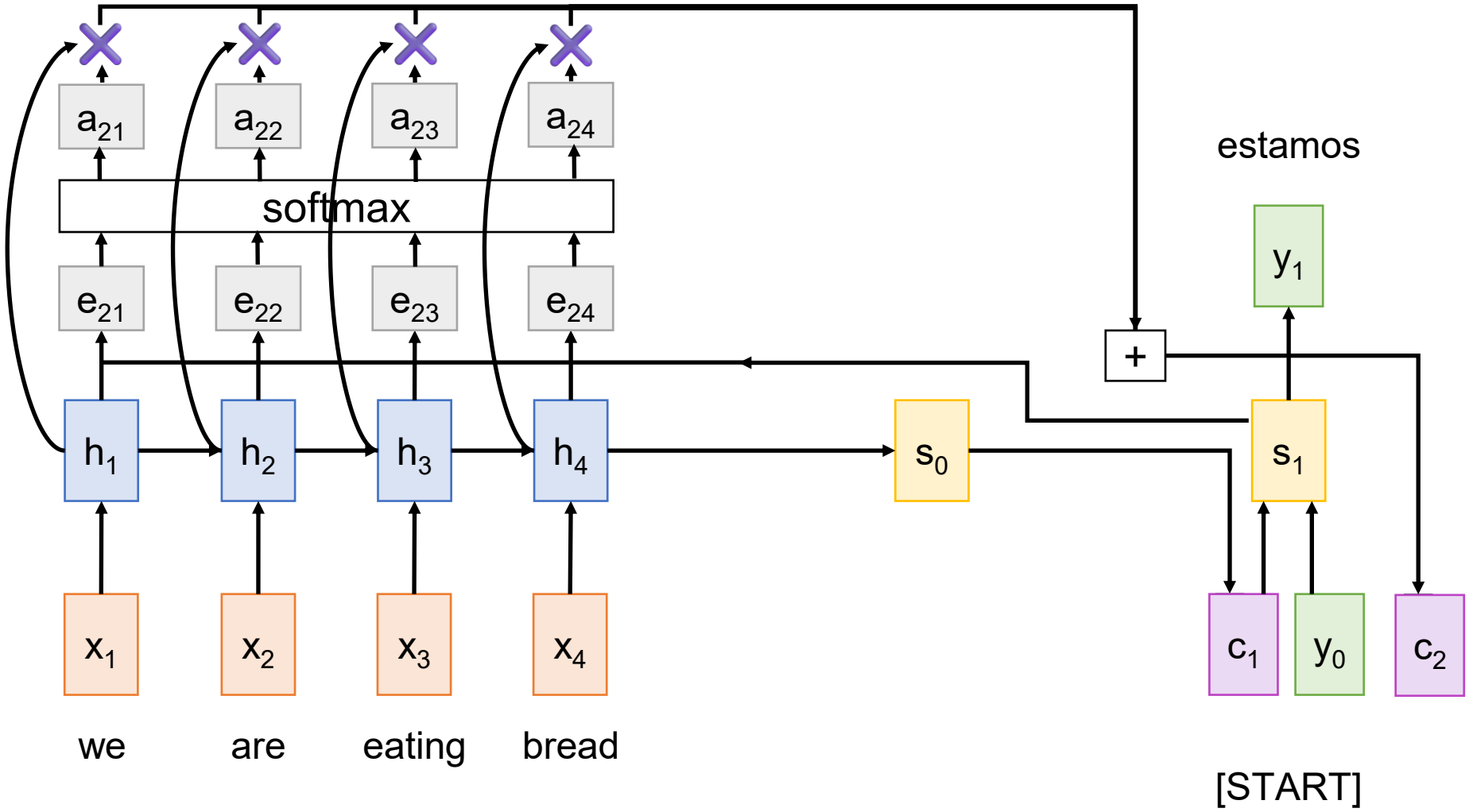
Set context vector **c** to a linear combination of hidden states
$c_t = \sum_i a_{t,i} h_i$

Bahdanau et al, "Neural machine translation by jointly learning to align and translate", ICLR 2015

This is an inductive bias we think is reasonable for this task. Need to verify

Slide credit: Justin Johnson

Machine Translation with RNNs **and Attention**

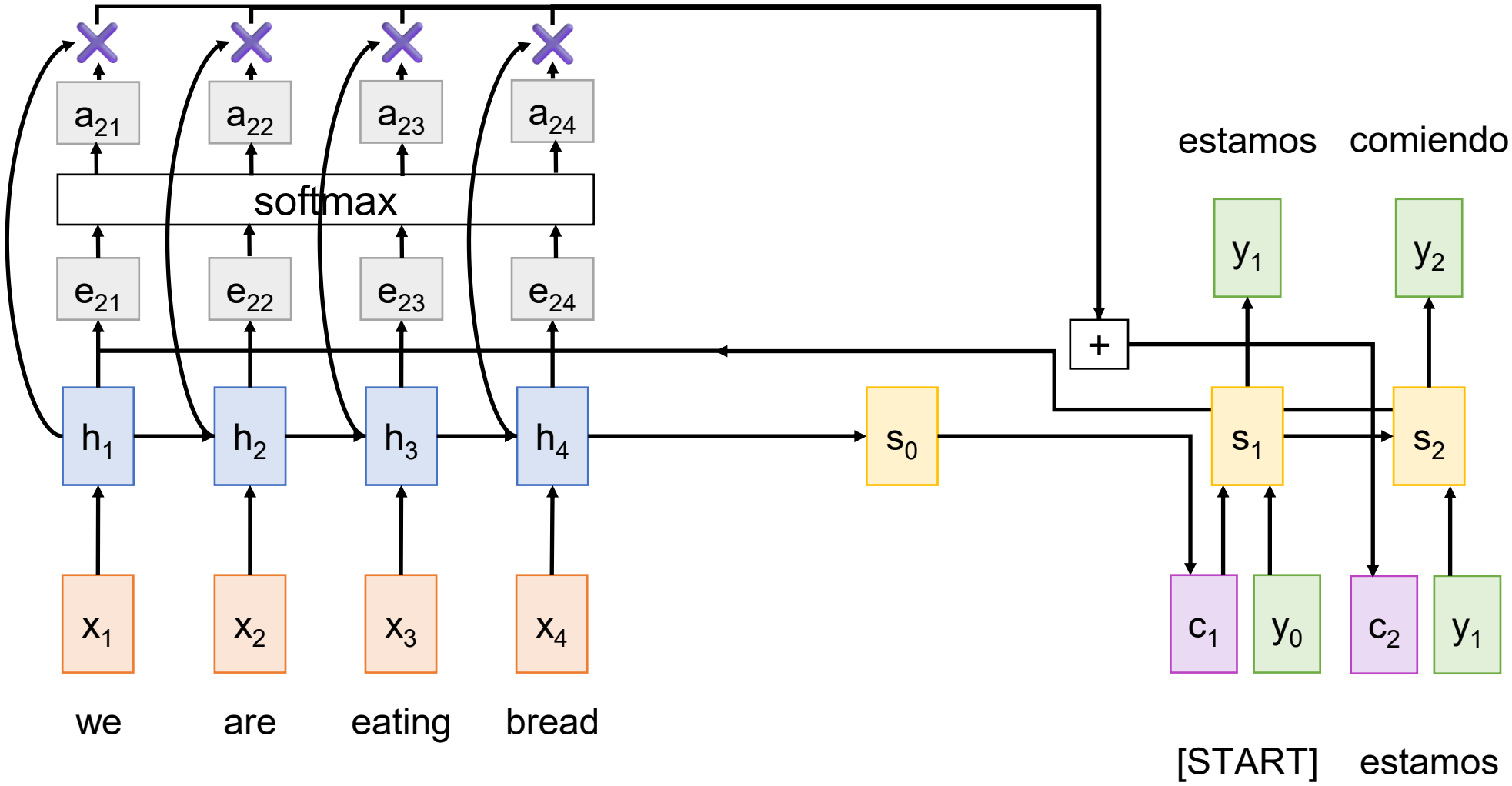


Repeat: Use s_1 to compute new context vector c_2

Bahdanau et al, “Neural machine translation by jointly learning to align and translate”, ICLR 2015

Slide credit: Justin Johnson

Machine Translation with RNNs **and Attention**



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Use c_2 to compute s_2, y_2

Bahdanau et al, "Neural machine translation by jointly learning to align and translate", ICLR 2015

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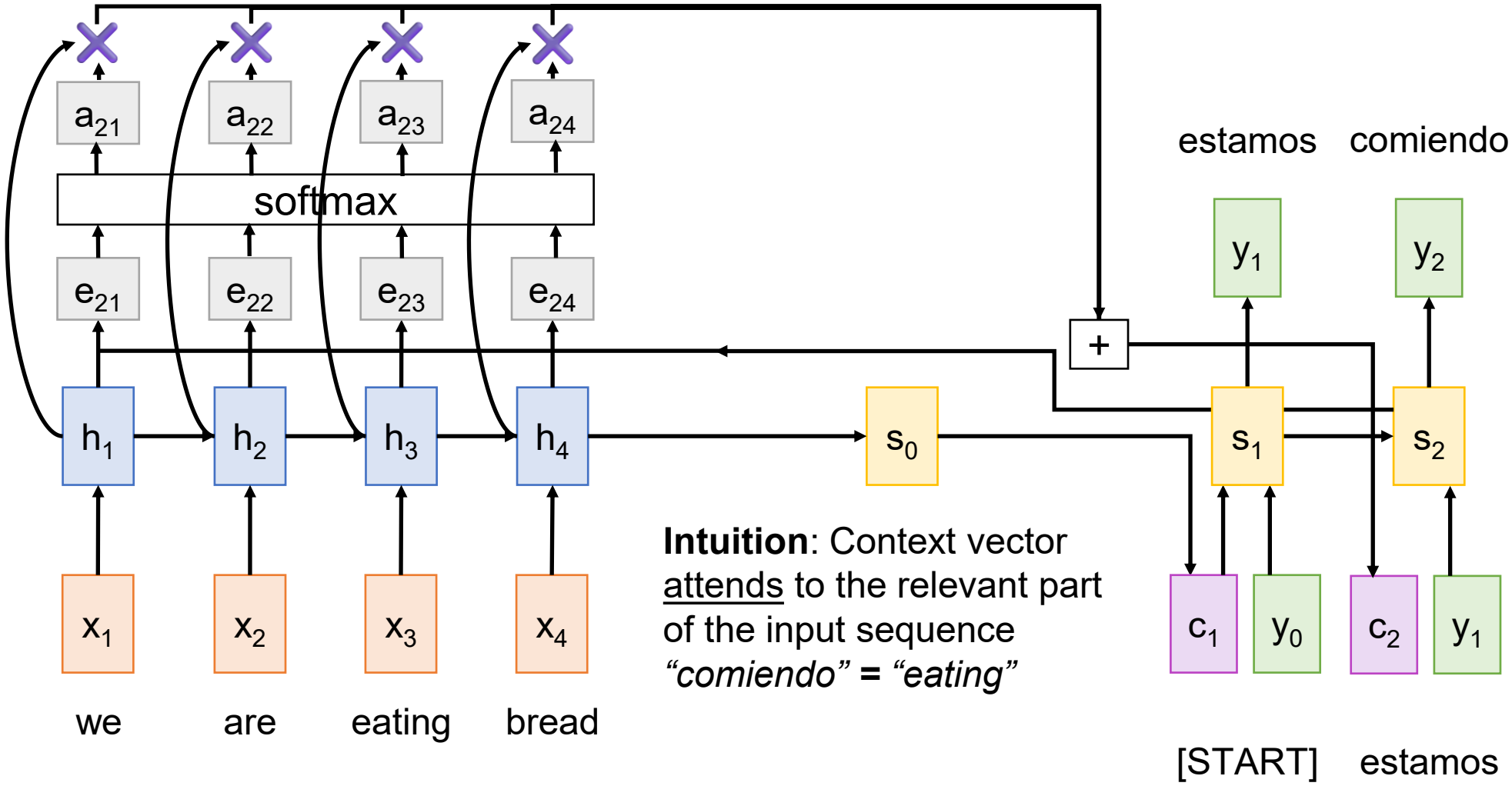

Intuition: Context vector attends to the relevant part of the input sequence
"comiendo" = "eating"

Repeat: Use s_1 to compute new context vector c_2

Use c_2 to compute s_2, y_2

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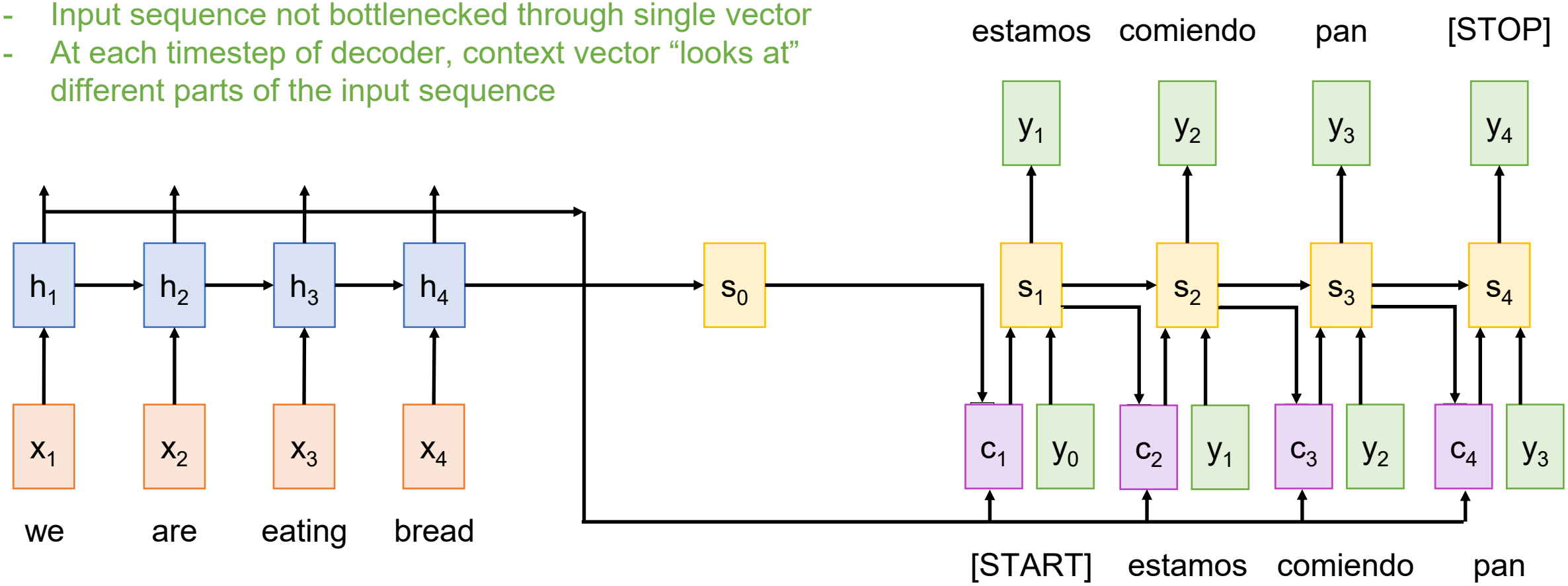
Slide credit: Justin Johnson

Machine Translation with RNNs **and Attention**

Use a different context vector in each timestep of decoder
- Input sequence not bottlenecked through single vector
- At each timestep of decoder, context vector "looks at" different parts of the input sequence



Bahdanau et al, "Neural machine translation by jointly learning to align and translate", ICLR 2015

Slide credit: Justin Johnson

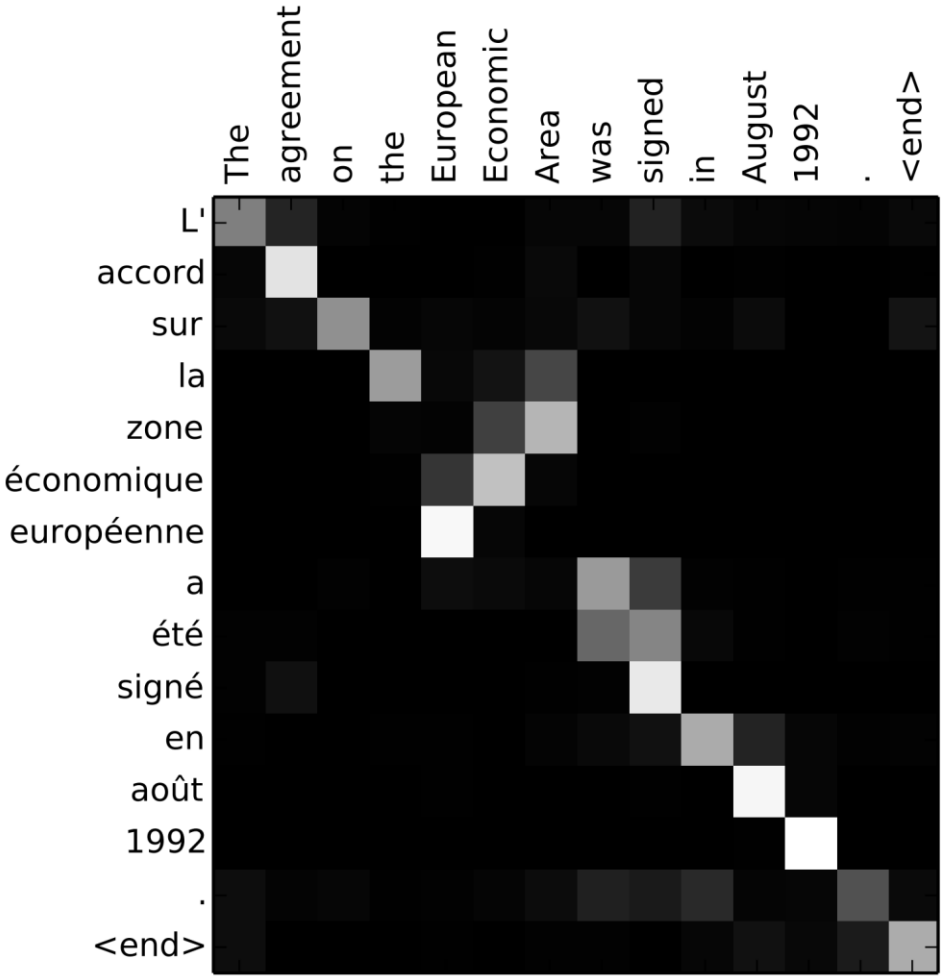
Machine Translation with RNNs **and Attention**

Example: English to French translation

Input: “The agreement on the European Economic Area was signed in August 1992.”

Output: “L’accord sur la zone économique européenne a été signé en août 1992.”

Visualize attention weights $a_{t,i}$



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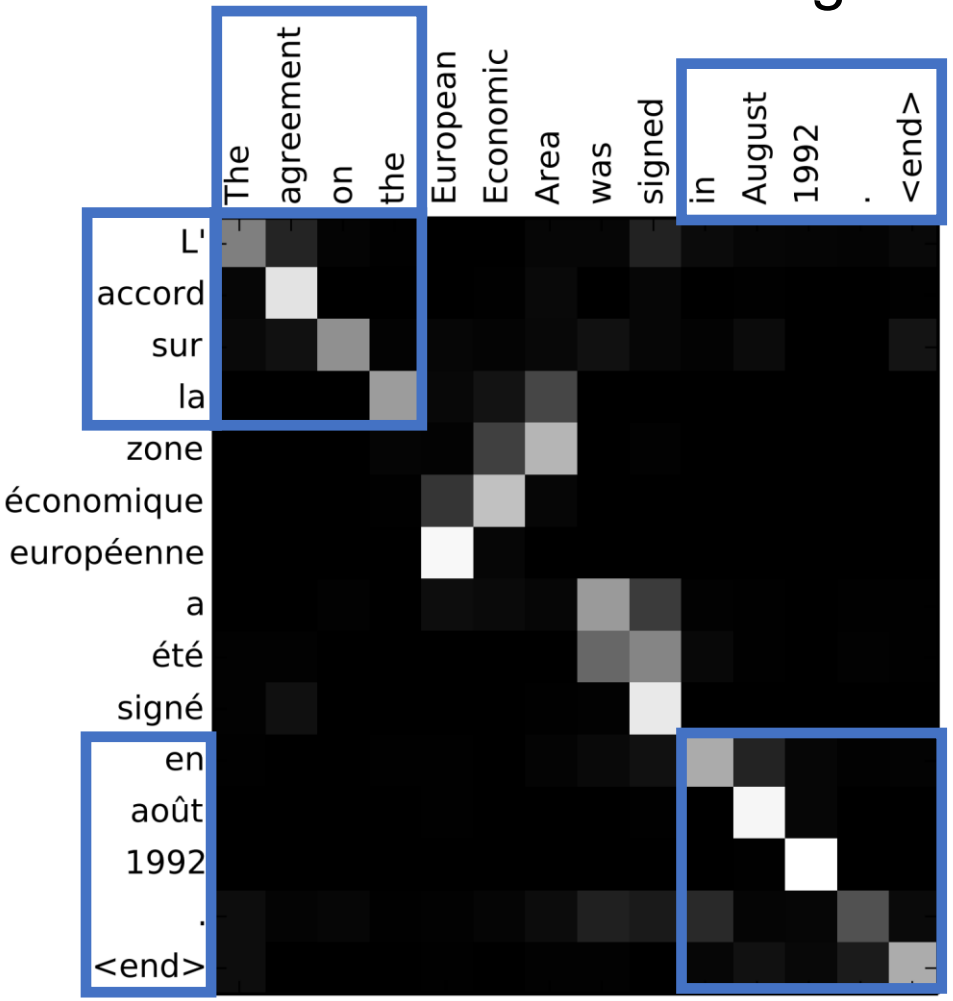

Diagonal attention means words correspond in order

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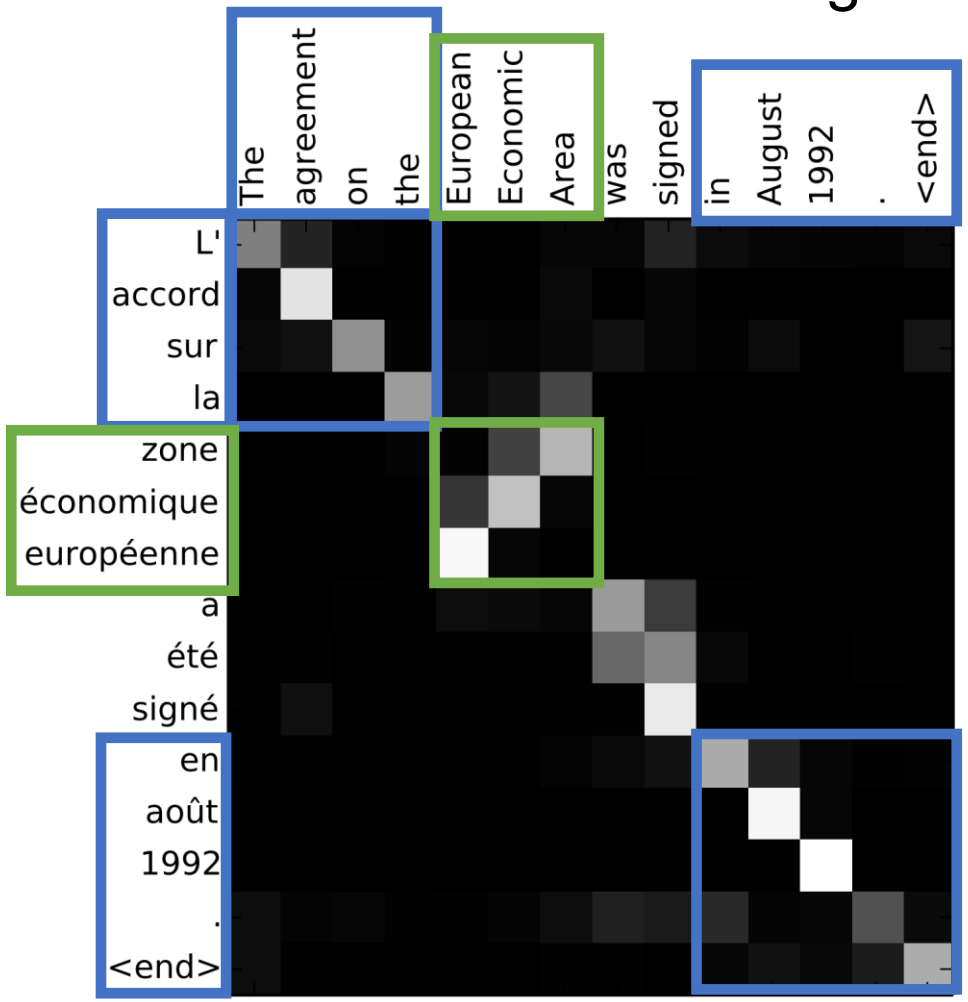

Diagonal attention means words correspond in order

Attention figures out different word orders

Diagonal attention means words correspond in order

Bahdanau et al, "Neural machine translation by jointly learning to align and translate", ICLR 2015

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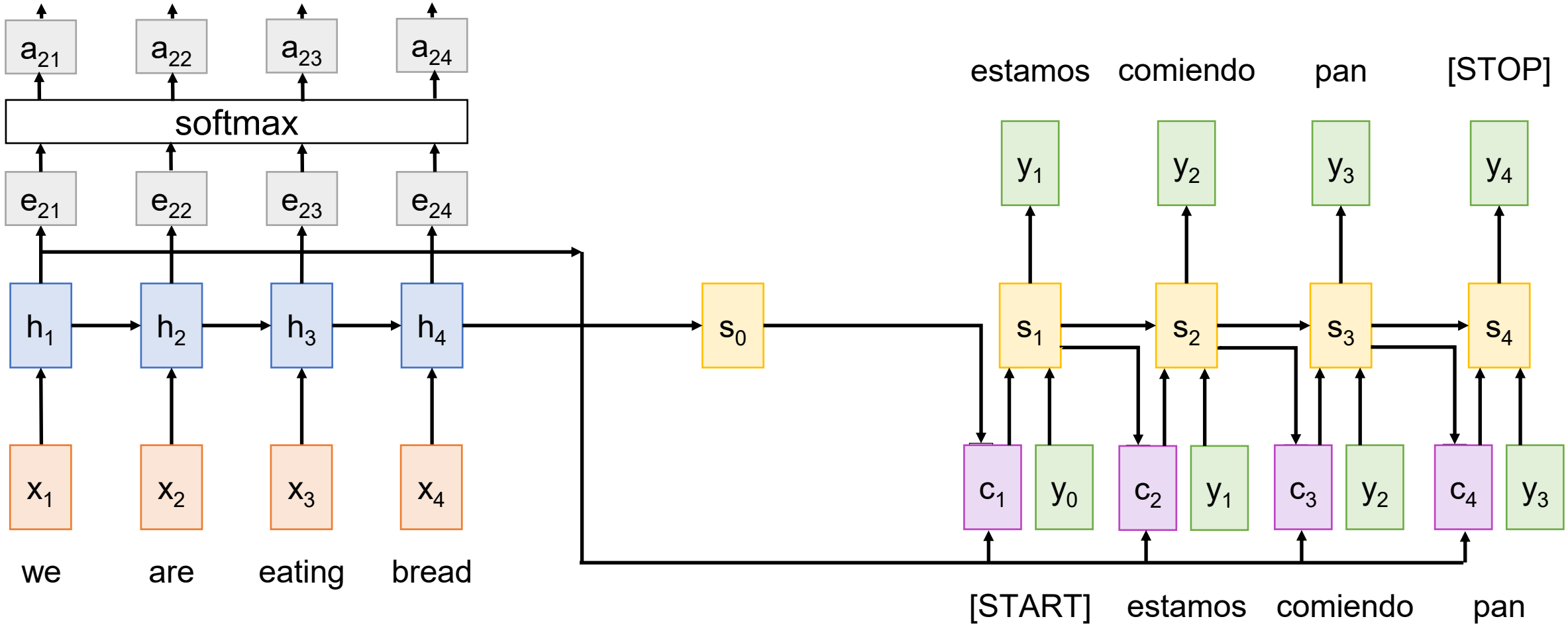
Machine Translation with RNNs **and Attention**



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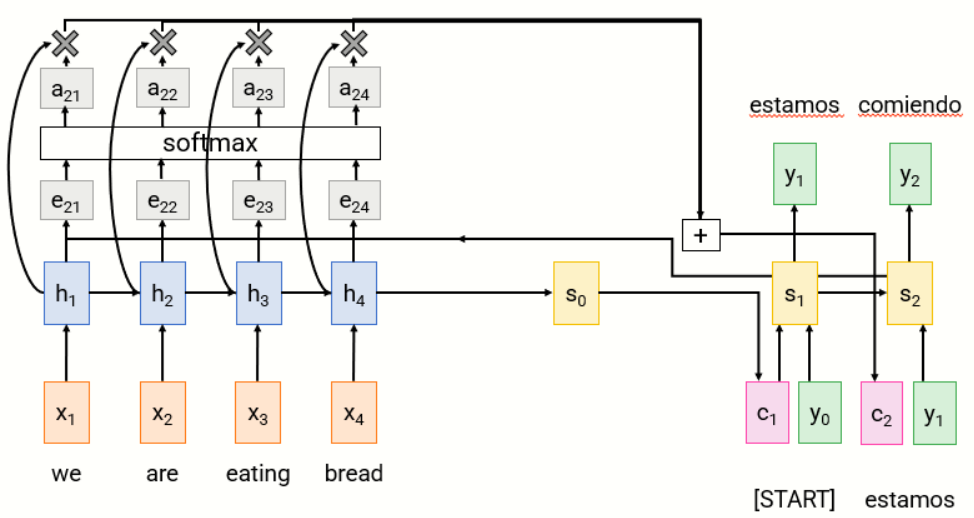

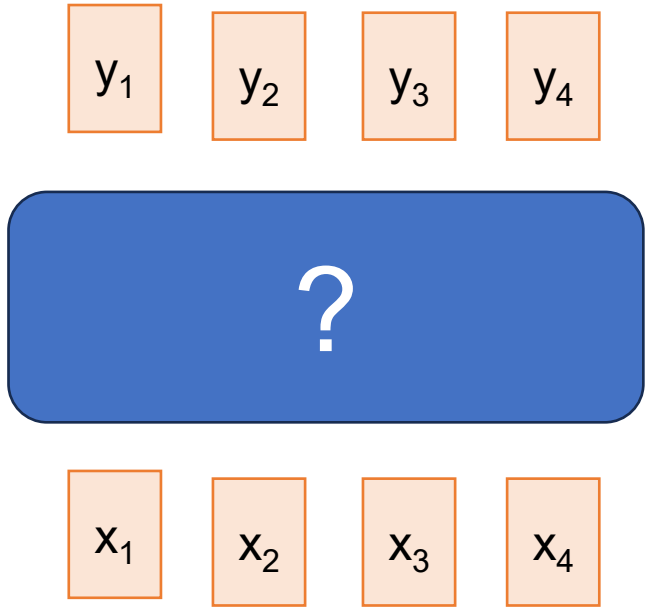

Idea: Can we use **attention** as a fundamental building block for a generic sequence (input) to sequence (output) layer?

Note: We just want a generic sequence-in, sequence-out model that will represent each input *contextualized* with rest of inputs, and encode meaning of entire sequence

We will progressively develop a generic mechanism using idea of attention. Don't try to map to RNN translation example!