Deep Learning
Sequence to Sequence models: Attention Models

Sequence-to-sequence modelling

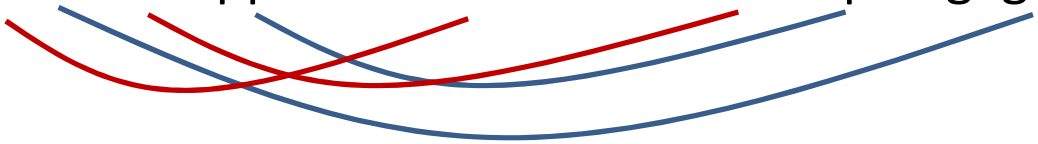
- Problem:
  - A sequence $X_1 \ldots X_N$ goes in
  - A different sequence $Y_1 \ldots Y_M$ comes out
- E.g.
  - Speech recognition: Speech goes in, a word sequence comes out
    - Alternately output may be phoneme or character sequence
  - Machine translation: Word sequence goes in, word sequence comes out
- In general $N \neq M$
  - No synchrony between X and Y.

Sequence to sequence

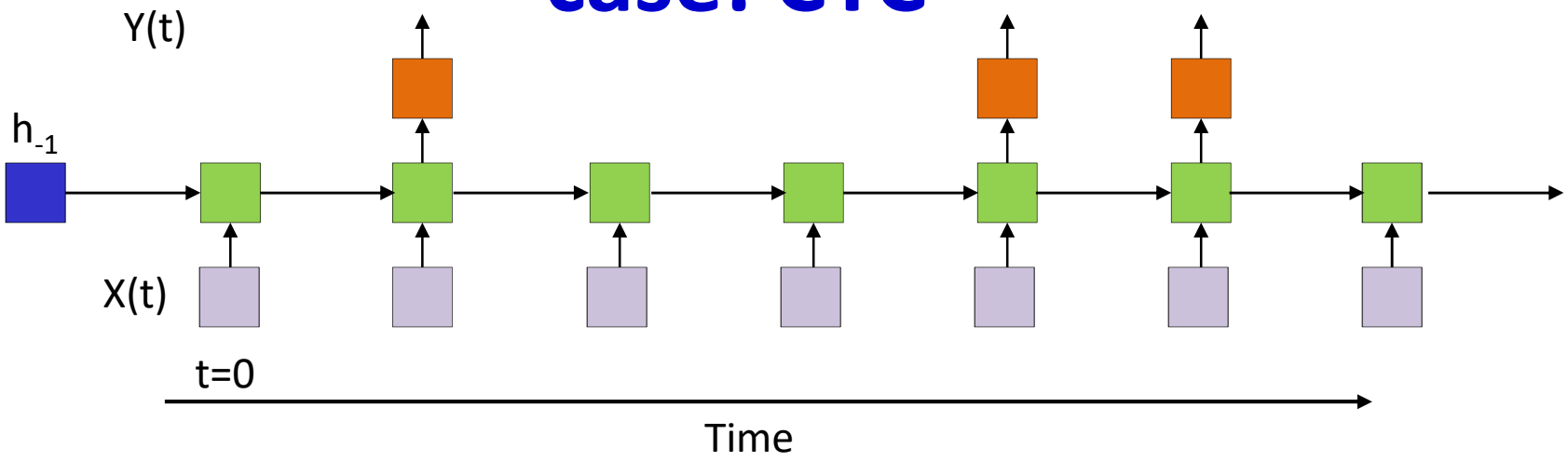
Seq2seq → I ate an apple

I ate an apple → Seq2seq → Ich habe einen apfel gegessen

- Sequence goes in, sequence comes out
- No notion of "synchrony" between input and output
  - May even not have a notion of "alignment"
    - E.g. "I ate an apple" → "Ich habe einen apfel gegessen"

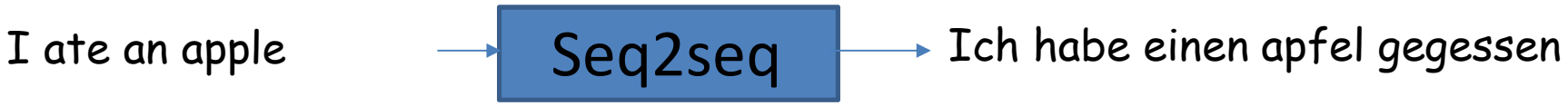


Recap: Have dealt with the "aligned" case: CTC



- The input and output sequences happen in the same order
  - Although they may be asynchronous
  - E.g. Speech recognition
    - The input speech corresponds to the phoneme sequence output

Today



- Sequence goes in, sequence comes out
- No notion of "synchrony" between input and output
  - May even not have a notion of "alignment"
    - E.g. "I ate an apple" → "Ich habe einen apfel gegessen"

Brief detour: Language models

- Modelling language using time-synchronous nets

- More generally language models and embeddings..

Which open source project?

```
/*
 * Increment the size file of the new incorrect UI_FILTER group information
 * of the size generatively.
 */
static int indicate_policy(void)
{
  int error;
  if (fd == MARN_EPT) {
    /*
     * The kernel blank will coeld it to userspace.
     */
    if (ss->segment < mem_total)
      unblock_graph_and_set_blocked();
    else
      ret = 1;
    goto bail;
  }
  segaddr = in_SB(in.addr);
  selector = seg / 16;
  setup_works = true;
  for (i = 0; i < blocks; i++) {
    seq = buf[i++];
    bpf = bd->bd.next + i * search;
    if (fd) {
      current = blocked;
    }
  }
  rw->name = "Getjbbregs";
  bprm_self_clearl(&iv->version);
  regs->new = blocks[(BPF_STATS << info->historidac)] | PFMR_CLOBATHINC_SECON
  return segtable;
}
```

Language modelling using RNNs

Four score and seven years ???

A B R A H A M L I N C O L ??

- Problem: Given a sequence of words (or characters) predict the next one

Language modelling: Representing words

- Represent words as one-hot vectors
  - Pre-specify a vocabulary of N words in fixed (e.g. lexical) order
    - *E.g. [A AARDVARK AARON ABACK ABACUS… ZZYP]*
  - Represent each word by an N-dimensional vector with N-1 zeros and a single 1 (in the position of the word in the ordered list of words)
    - E.g. "AARDVARK" → [0 1 0 0 0 …]
    - E.g. "AARON" → [0 0 1 0 0 0 …]

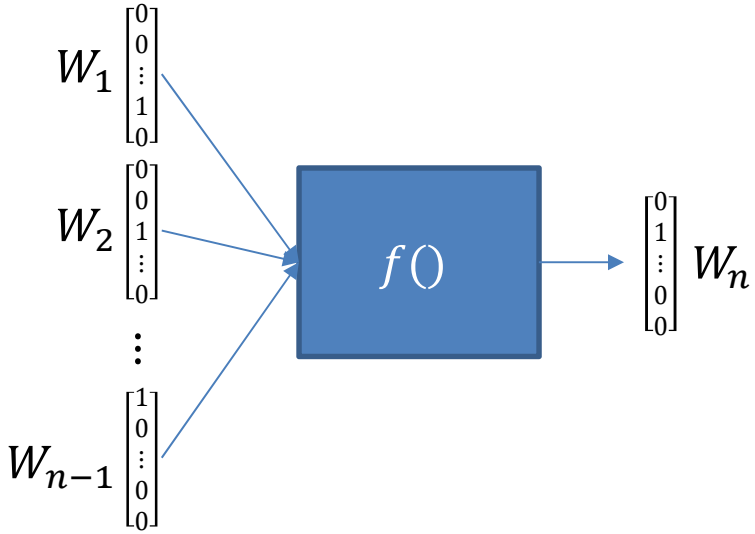
- Characters can be similarly represented
  - English will require about 100 characters, to include both cases, special characters such as commas, hyphens, apostrophes, etc., and the space character

Predicting words

Four score and seven years ???

$W_n = f(\text{W\_1}, W_1, \ldots, W_{n-1})$

Nx1 one-hot vectors



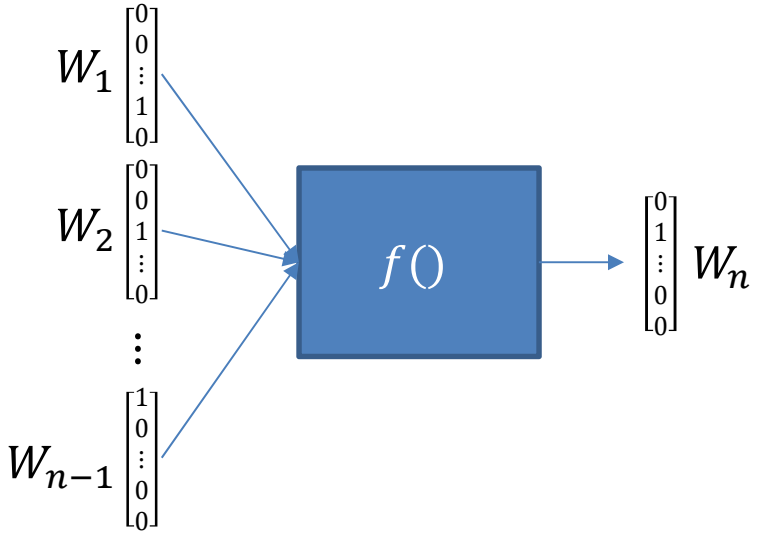
- Given one-hot representations of $W_1 \ldots W_{n-1}$, predict W_n

Predicting words

Four score and seven years ???

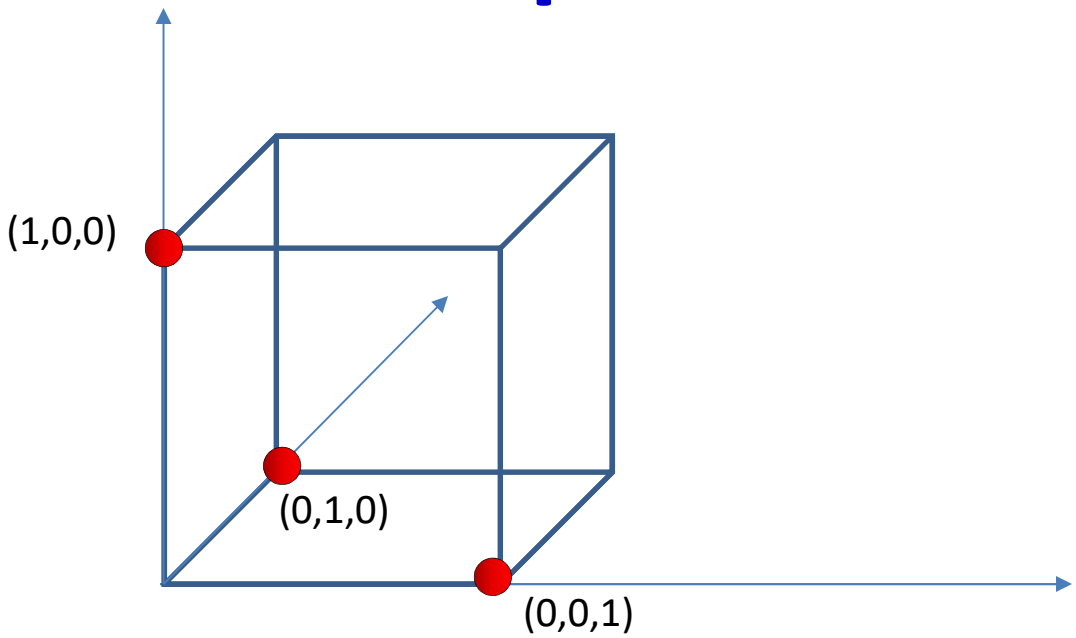
$W_n = f(\text{W\_1}, W_1, \ldots, W_{n-1})$

Nx1 one-hot vectors



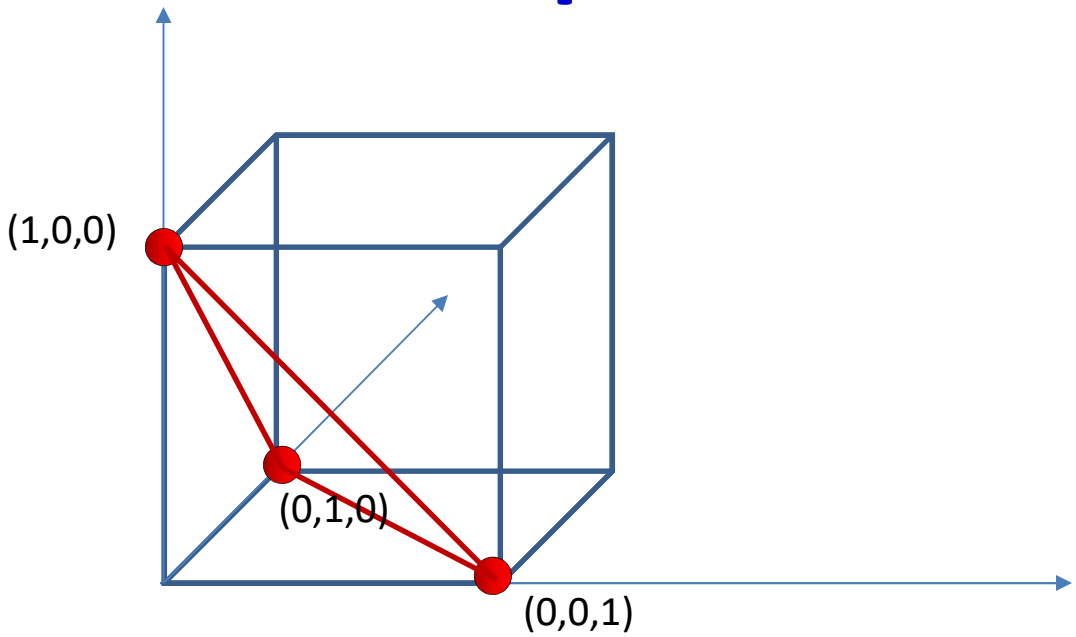
- Given one-hot representations of $W_1 \ldots W_{n-1}$, predict W_n
- **Dimensionality problem:** All inputs $W_1 \ldots W_{n-1}$ are both very high-dimensional and very sparse

The one-hot representation



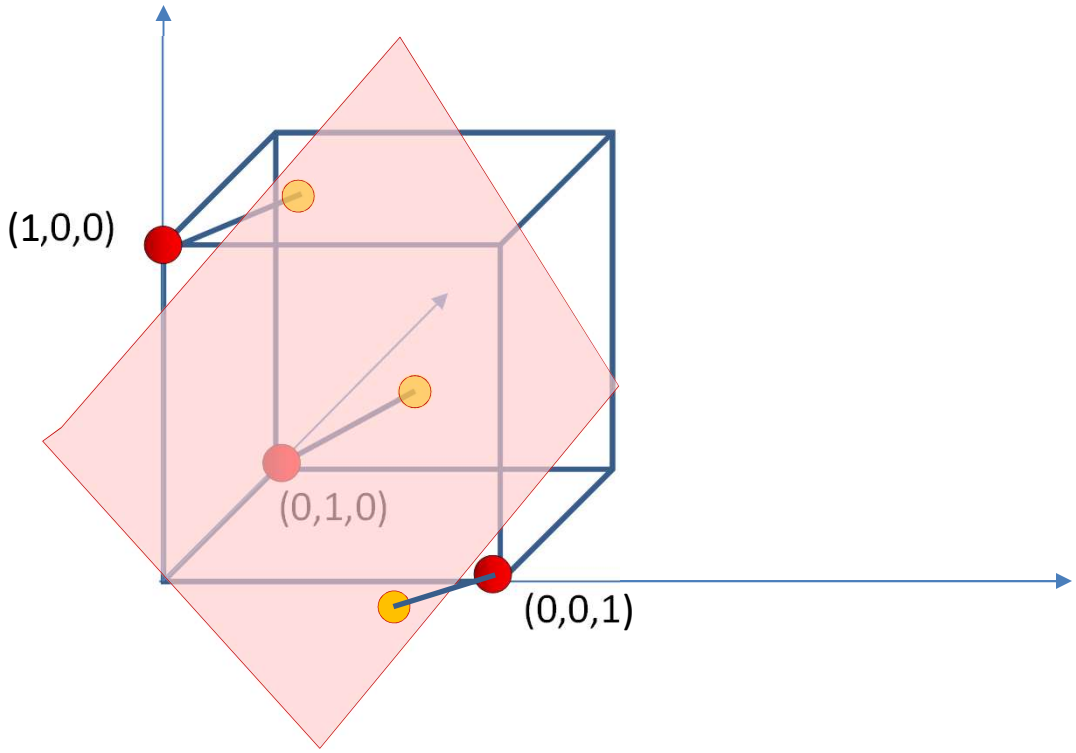
- The one hot representation uses only N corners of the 2^N corners of a unit cube
  - Actual volume of space used = 0
    - $(1, \varepsilon, \delta)$ has no meaning except for $\varepsilon = \delta = 0$
  - Density of points: $\mathcal{O}\left(\frac{N}{r^N}\right)$
- This is a tremendously inefficient use of dimensions

Why one-hot representation



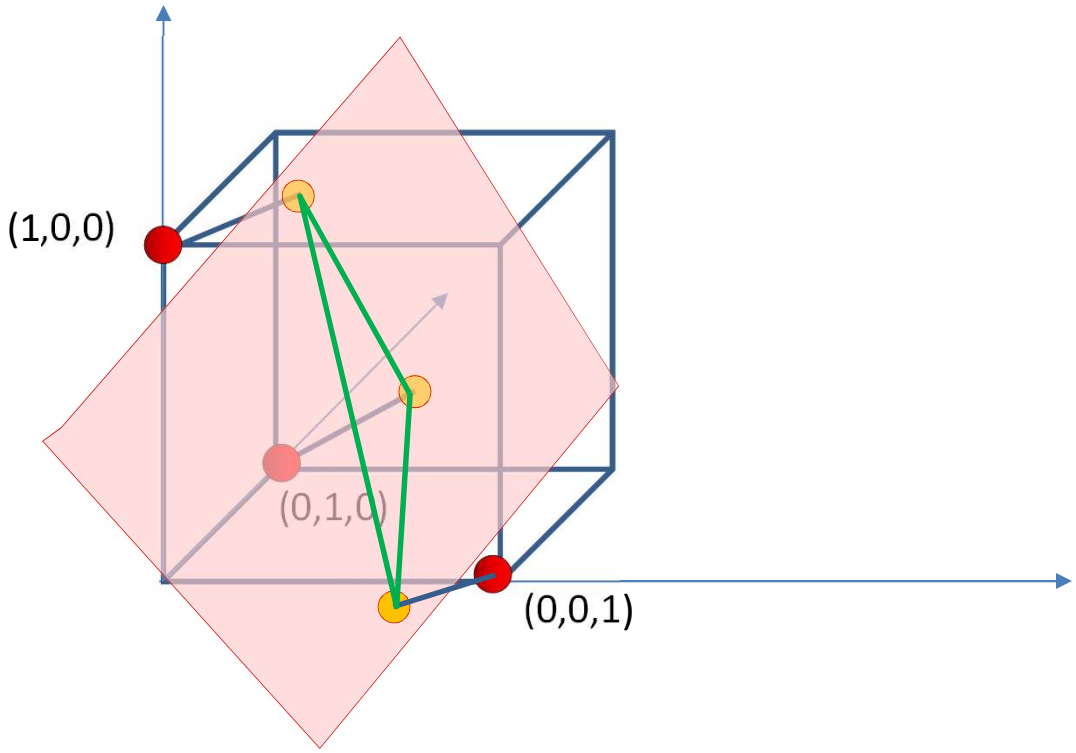
- The one-hot representation makes no assumptions about the relative importance of words
  - All word vectors are the same length
- It makes no assumptions about the relationships between words
  - The distance between every pair of words is the same

Solution to dimensionality problem



- Project the points onto a lower-dimensional subspace
  - The volume used is still 0, but density can go up by many orders of magnitude
    - Density of points: $\mathcal{O}\left(\frac{N}{r^M}\right)$

Solution to dimensionality problem

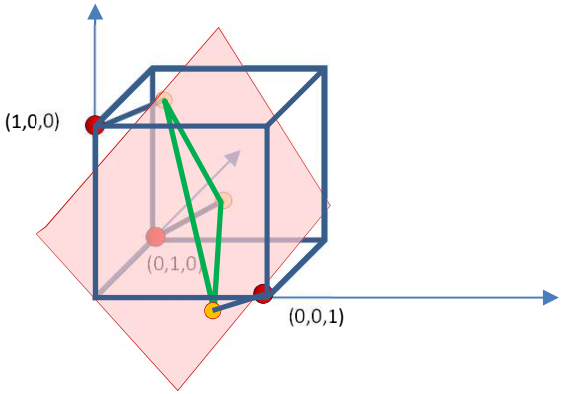


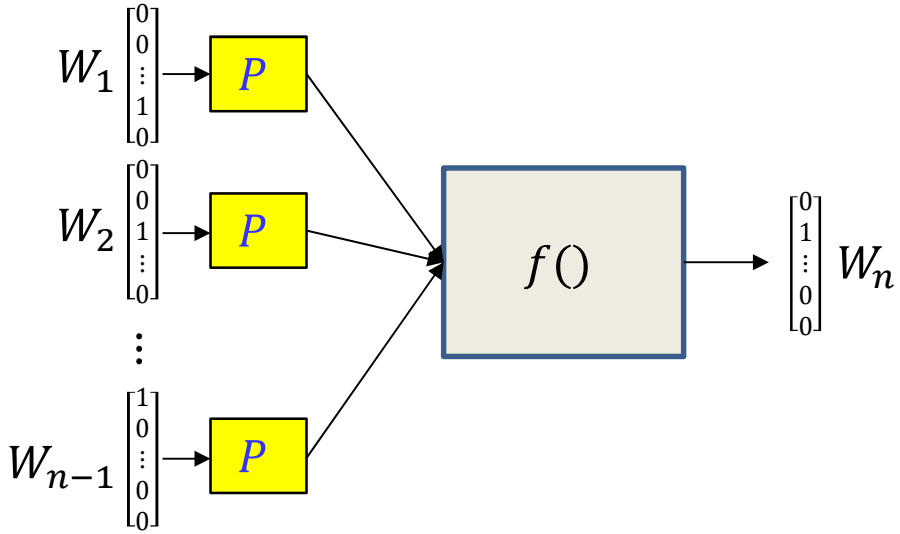
- Project the points onto a lower-dimensional subspace
  - The volume used is still 0, but density can go up by many orders of magnitude
    - Density of points: $\mathcal{O}\left(\frac{N}{r^M}\right)$
  - If properly learned, the distances between projected points will capture semantic relations between the words
    - This will also require linear transformation (stretching/shrinking/rotation) of the subspace

The *Projected* word vectors

Four score and seven years ???

$$W_n = f(PW_1, PW_2, \ldots, PW_{n-1})$$

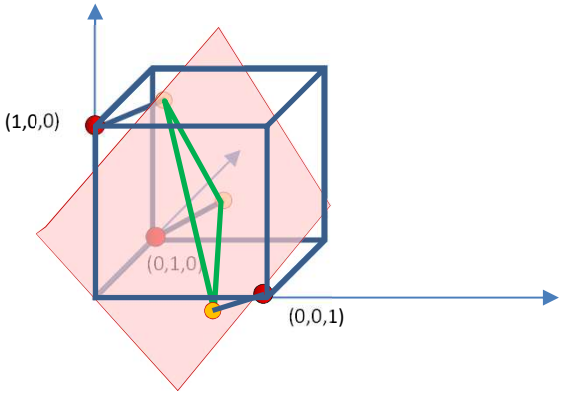


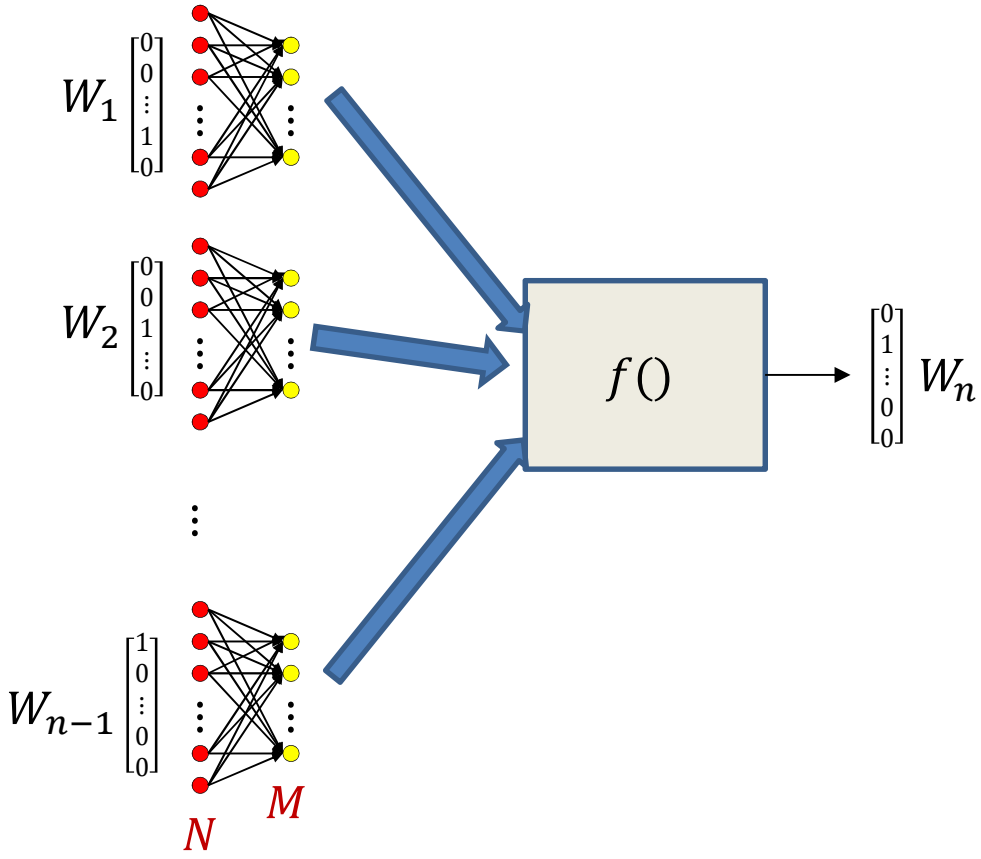


- *Project* the N-dimensional one-hot word vectors into a lower-dimensional space
  - Replace every one-hot vector W_i by PW_i
  - P is an $M \times N$ matrix
  - PW_i is now an M-dimensional vector
  - *Learn P* using an appropriate objective
    - Distances in the projected space will reflect relationships imposed by the objective

"Projection"

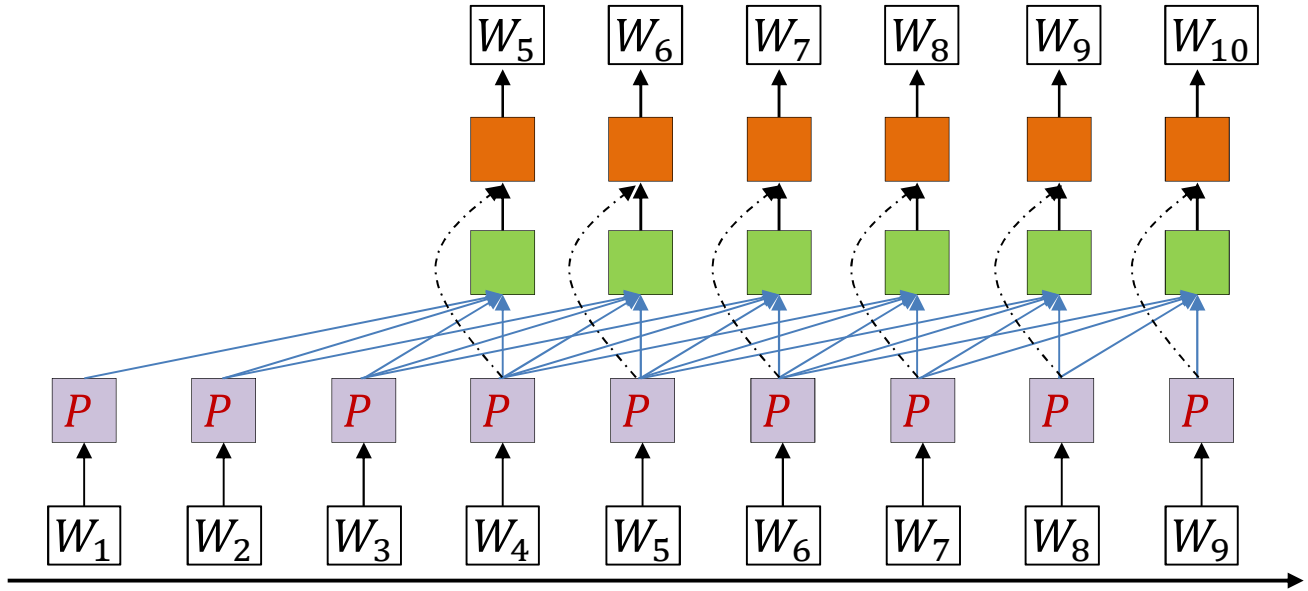
$$W_n = f(PW_1, PW_2, \ldots, PW_{n-1})$$





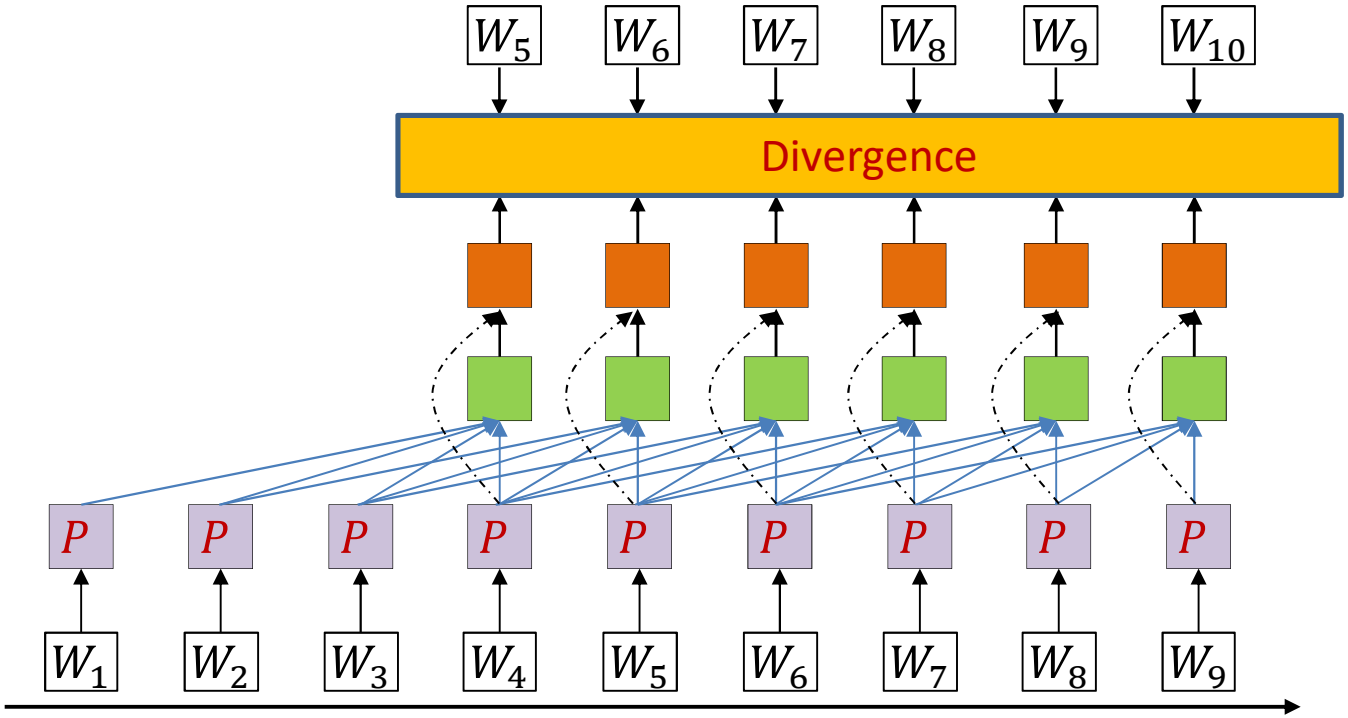
- *P* is a simple linear transform
- A single transform can be implemented as a layer of M neurons with linear activation
- The transforms that apply to the individual inputs are all M-neuron linear-activation subnets with tied weights

Predicting words: The TDNN model



- Predict each word based on the past N words
  - "A neural probabilistic language model", Bengio et al. 2003
  - Hidden layer has Tanh() activation, output is softmax

Training



- Input: symbols as one-hot vectors
  - Dimensionality of the vector is the size of the "vocabulary"
  - Projected down to lower-dimensional "embeddings"
- Output: Probability distribution over symbols

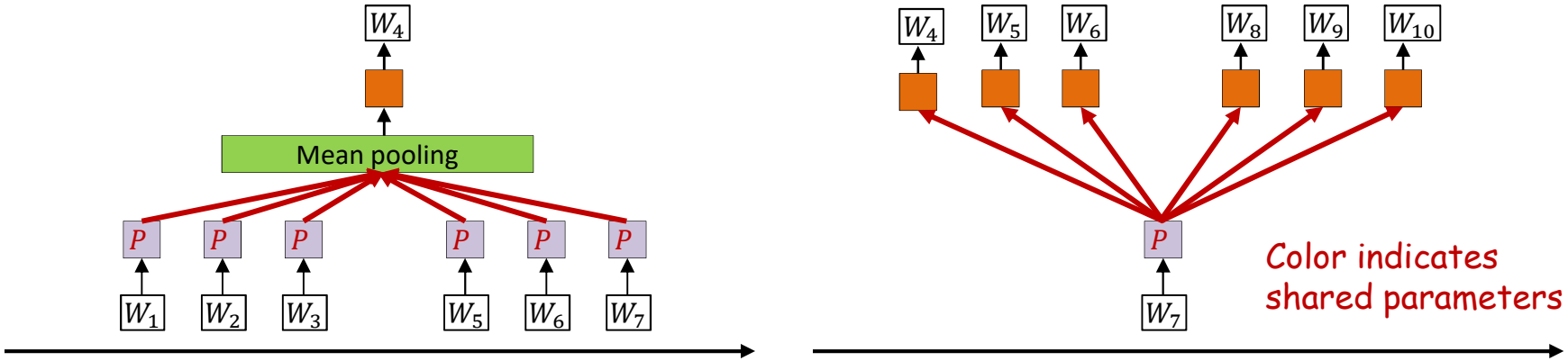
$$Y(t,i) = P(V_i | w_{t-k} \dots w_{t-1})$$

  - V_i is the i-th symbol in the vocabulary
- Divergence

$$Div\big(\mathbf{Y}_{target}(1 \dots T), \mathbf{Y}(1 \dots T)\big) = \sum_t Xent\big(\mathbf{Y}_{target}(t), \mathbf{Y}(t)\big) = -\sum_t \log Y(t, w_{t+1})$$

The probability assigned to the correct next word

Alternative models to learn projections



- Soft bag of words: Predict word based on words in immediate context
  - Without considering specific position
- Skip-grams: Predict adjacent words based on current word

Embeddings: Examples

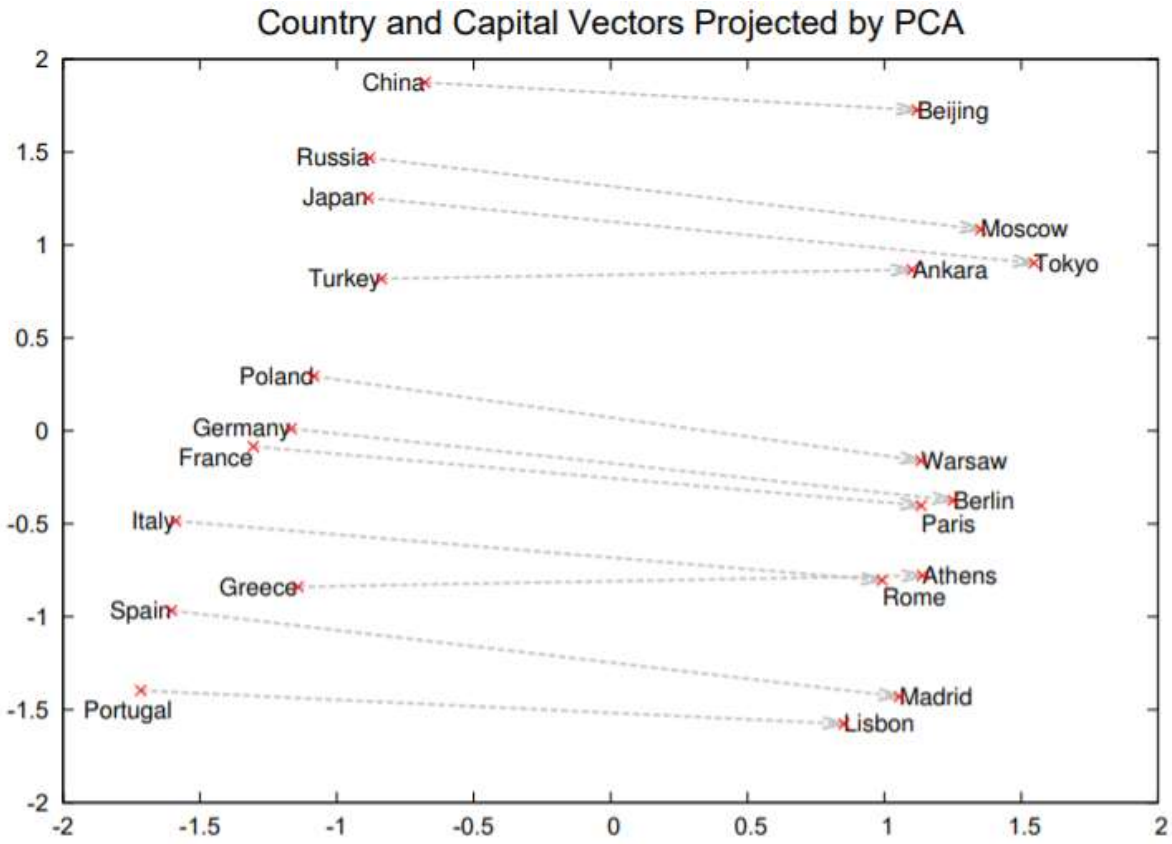
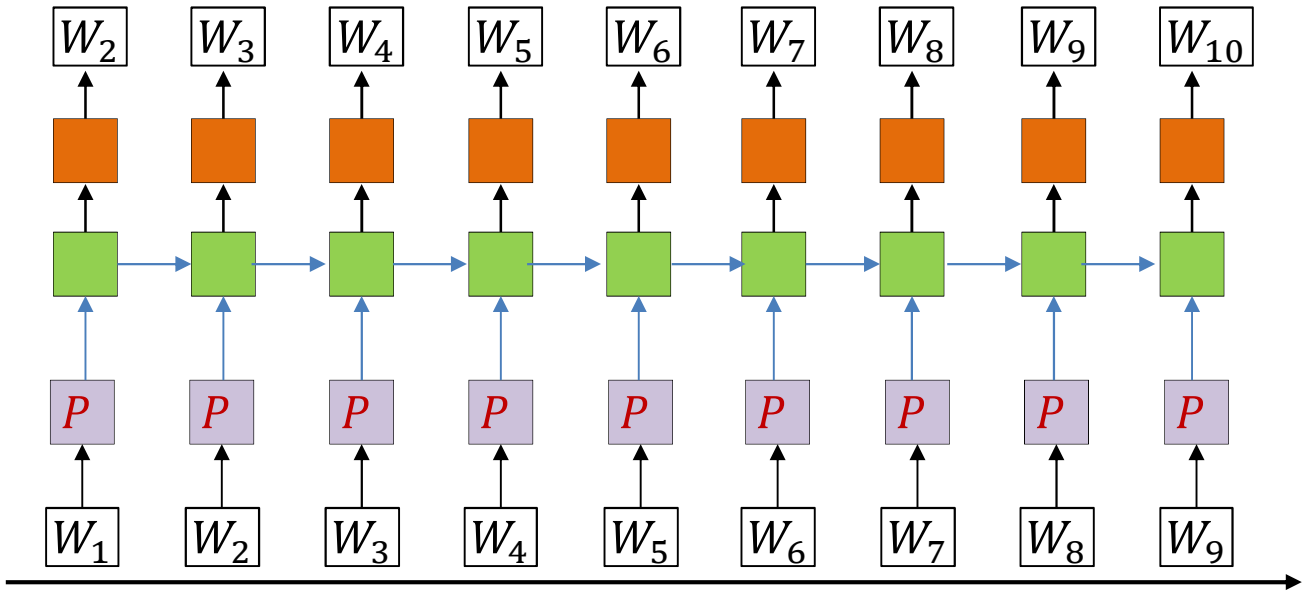


Figure 2: Two-dimensional PCA projection of the 1000-dimensional Skip-gram vectors of countries and their capital cities. The figure illustrates ability of the model to automatically organize concepts and learn implicitly the relationships between them, as during the training we did not provide any supervised information about what a capital city means.

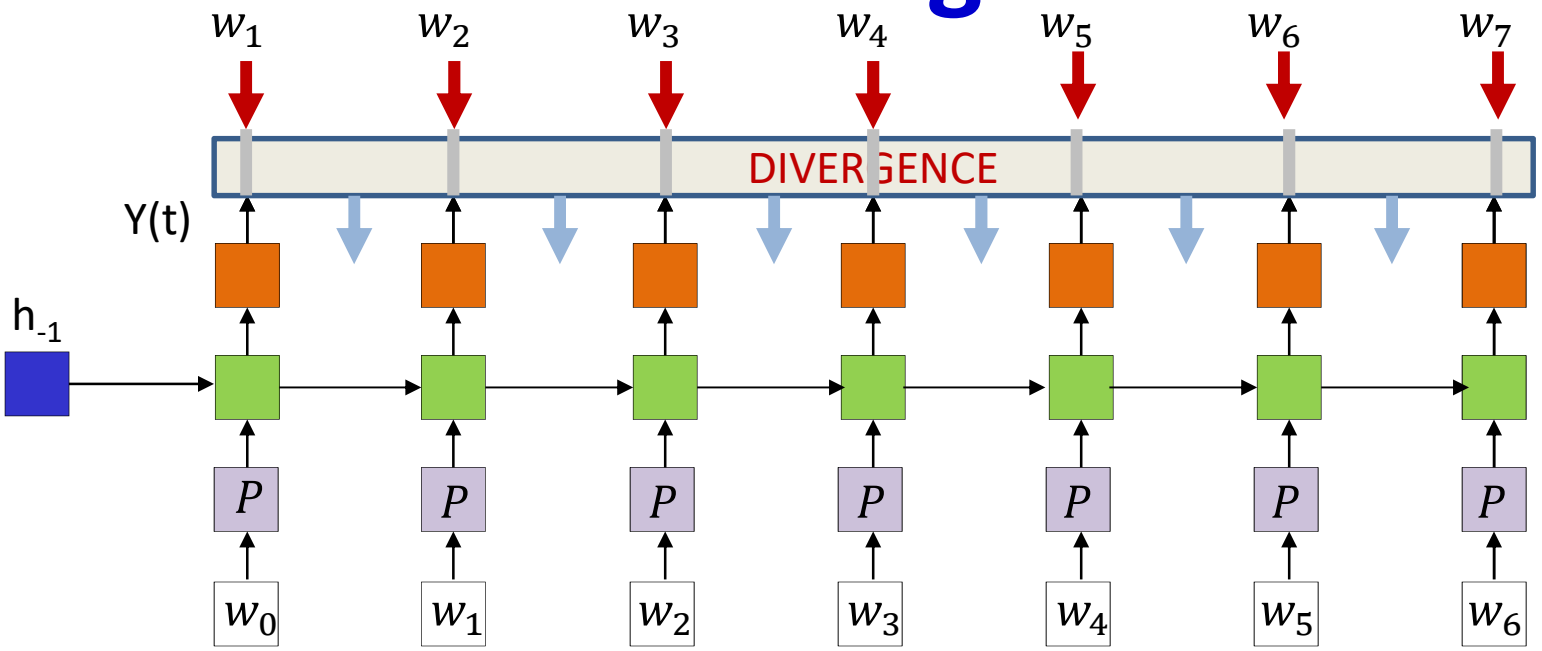
- From Mikolov et al., 2013, "Distributed Representations of Words and Phrases and their Compositionality"

Generating Language: The recurrent model



- The hidden units are (one or more layers of) LSTM units
- Trained via backpropagation from a lot of text

Training



- Input: symbols as one-hot vectors
  - Dimensionality of the vector is the size of the "vocabulary"
  - Projected down to lower-dimensional "embeddings"
- Output: Probability distribution over symbols

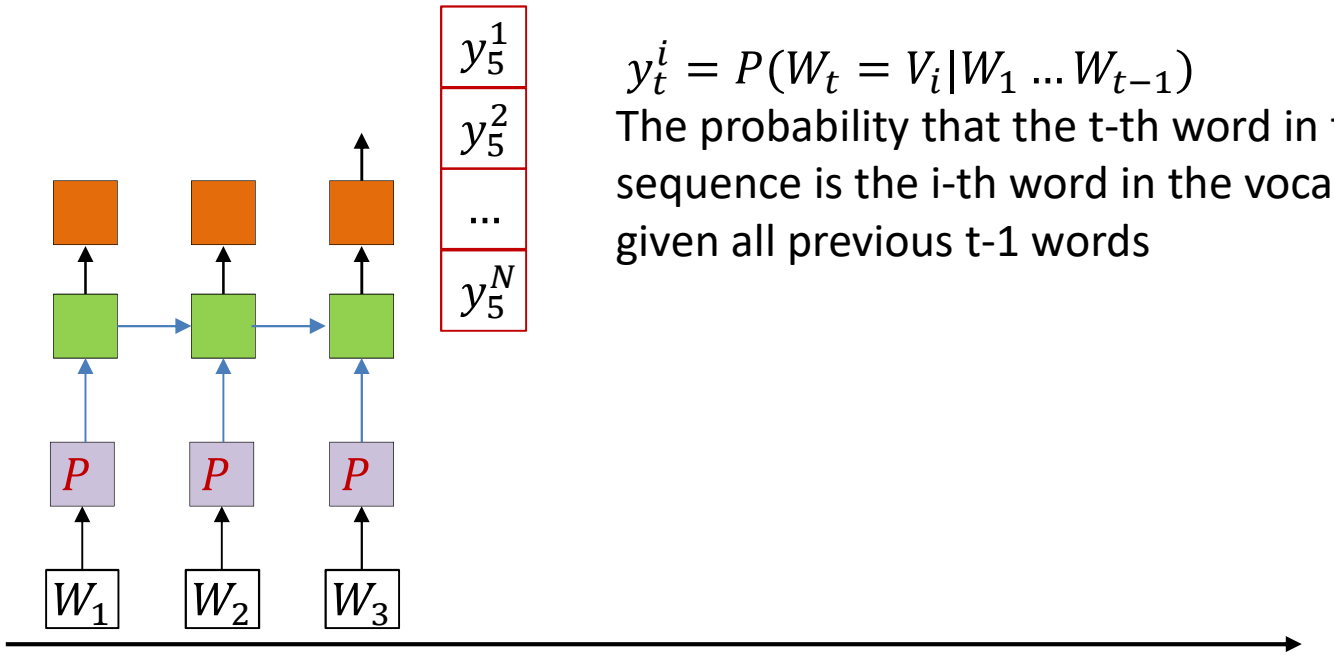
$$Y(t,i) = P(V_i | w_0 \dots w_{t-1})$$

  - V_i is the i-th symbol in the vocabulary
- Divergence

$$Div\big(\mathbf{Y}_{target}(1 \dots T), \mathbf{Y}(1 \dots T)\big) = \sum_t Xent\big(\mathbf{Y}_{target}(t), \mathbf{Y}(t)\big) = -\sum_t \log Y(t, w_{t+1})$$

The probability assigned to the correct next word

Generating Language: Synthesis

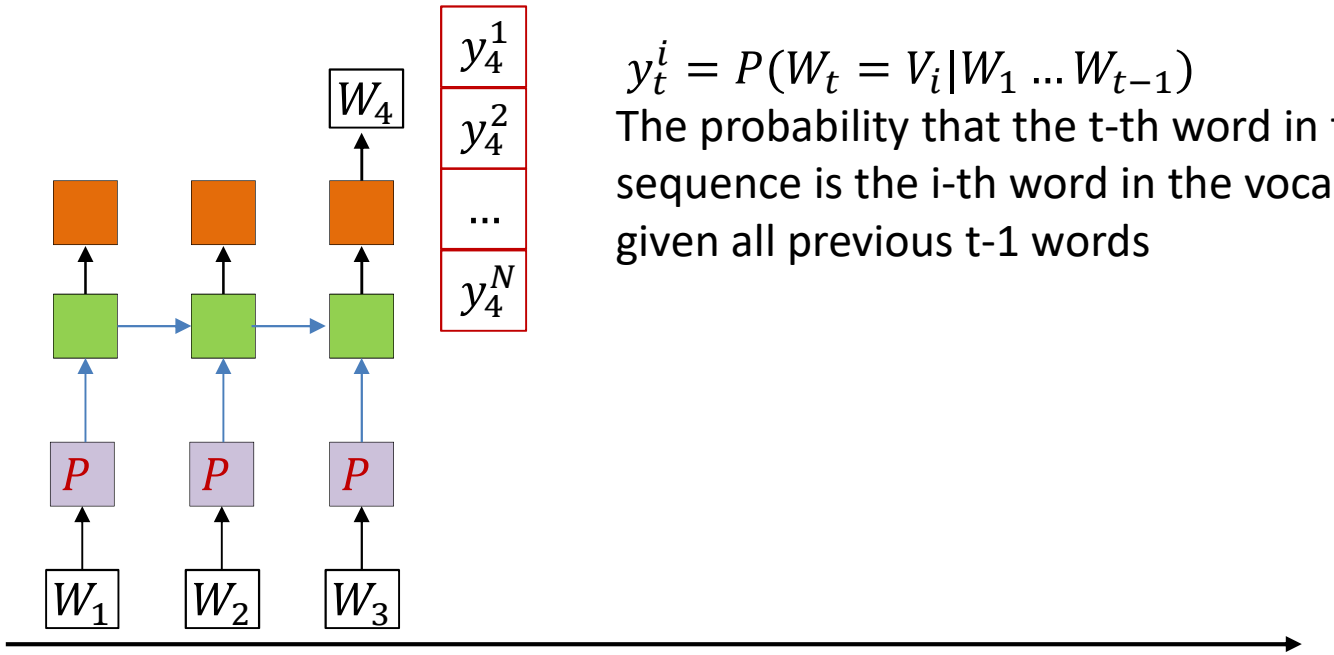


$y_t^i = P(W_t = V_i | W_1 \ldots W_{t-1})$

The probability that the t-th word in the sequence is the i-th word in the vocabulary given all previous t-1 words

- On trained model : Provide the first few words
  - One-hot vectors
- After the last input word, the network generates a probability distribution over words
  - Outputs an N-valued probability distribution rather than a one-hot vector

Generating Language: Synthesis

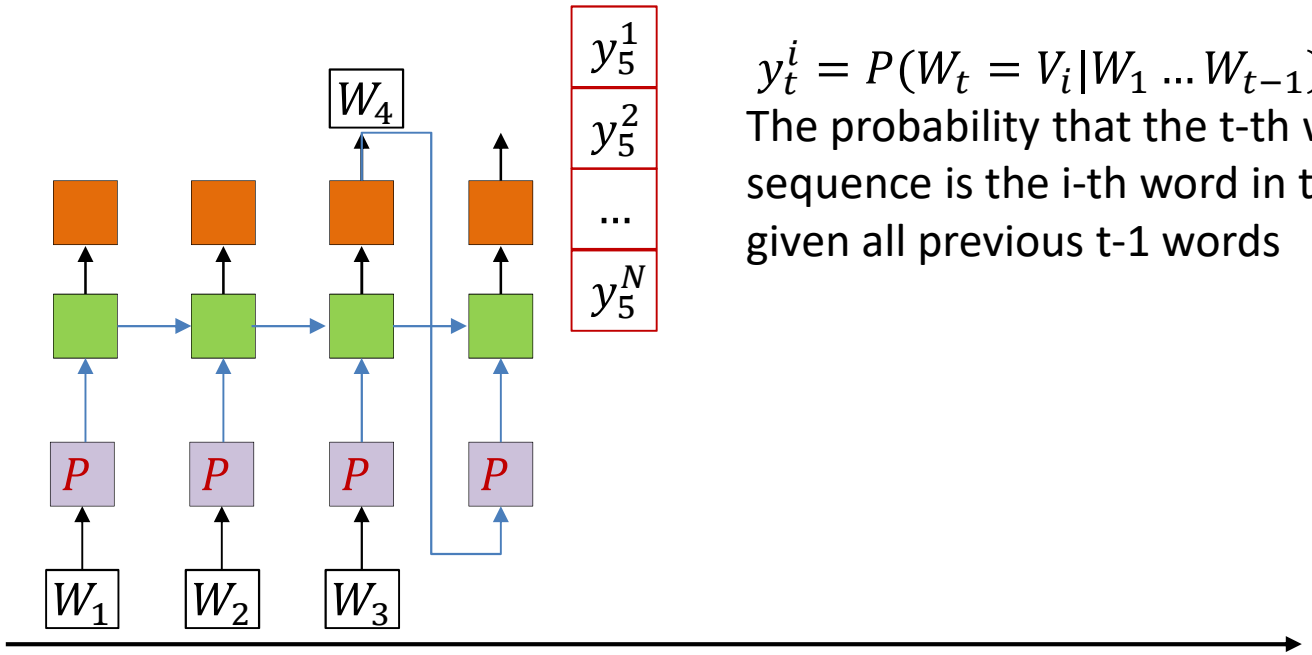


$y_t^i = P(W_t = V_i | W_1 \dots W_{t-1})$

The probability that the t-th word in the sequence is the i-th word in the vocabulary given all previous t-1 words

- Select the most likely word
  - Or draw sample from output distribution

Generating Language: Synthesis

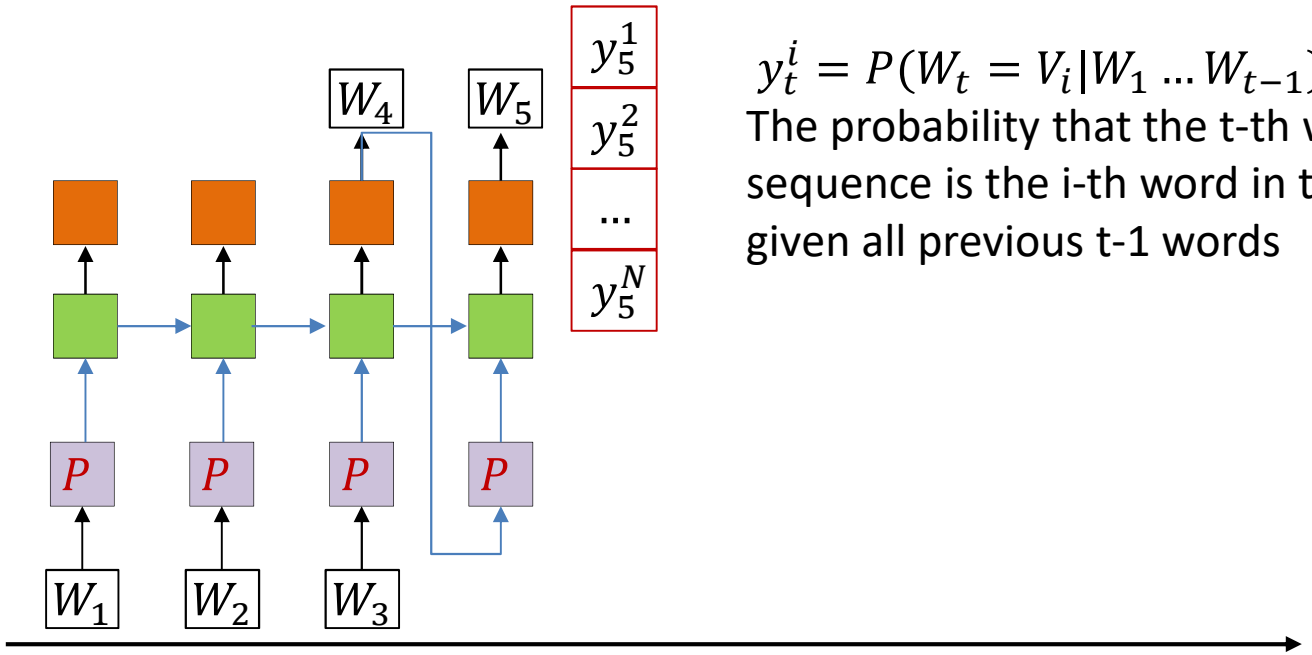


$y_t^i = P(W_t = V_i | W_1 \dots W_{t-1})$

The probability that the t-th word in the sequence is the i-th word in the vocabulary given all previous t-1 words

- Feed the drawn word as the next word in the series
  - And draw the next word from the output probability distribution

Generating Language: Synthesis

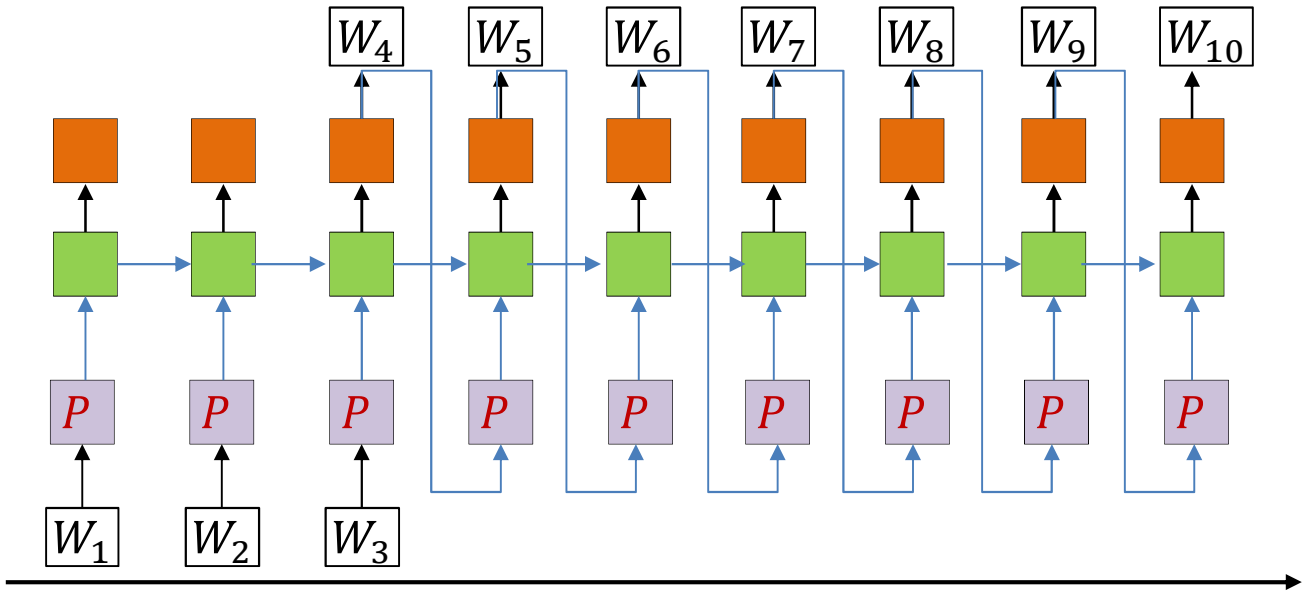


$y_t^i = P(W_t = V_i | W_1 \dots W_{t-1})$

The probability that the t-th word in the sequence is the i-th word in the vocabulary given all previous t-1 words

- Feed the drawn word as the next word in the series
  - And draw the next word from the output probability distribution

Generating Language: Synthesis



- Feed the drawn word as the next word in the series
  - And draw the next word from the output probability distribution
- Continue this process until we terminate generation
  - For text generation we will usually end at an <eos> (end of sequence) symbol
    - The <eos> symbol is a special symbol included in the vocabulary, which indicates the termination of a sequence and occurs only at the final position of sequences

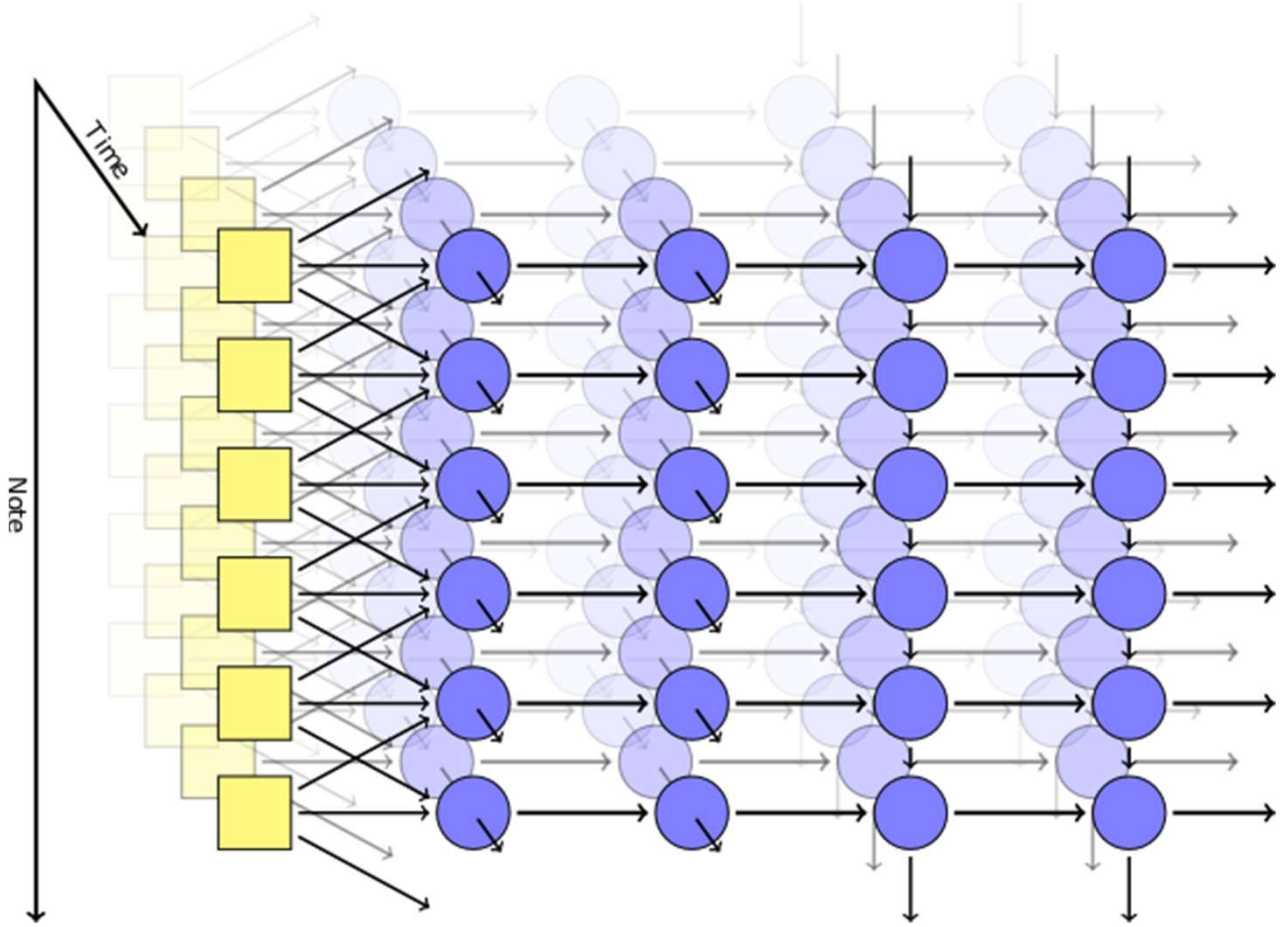
Which open source project?

```
/*
 * Increment the size file of the new incorrect UI_FILTER group information
 * of the size generatively.
 */
static int indicate_policy(void)
{
  int error;
  if (fd == MARN_EPT) {
    /*
     * The kernel blank will coeld it to userspace.
     */
    if (ss->segment < mem_total)
      unblock_graph_and_set_blocked();
    else
      ret = 1;
    goto bail;
  }
  segaddr = in_SB(in.addr);
  selector = seg / 16;
  setup_works = true;
  for (i = 0; i < blocks; i++) {
    seq = buf[i++];
    bpf = bd->bd.next + i * search;
    if (fd) {
      current = blocked;
    }
  }
  rw->name = "Getjbbregs";
  bprm_self_clearl(&iv->version);
  regs->new = blocks[(BPF_STATS << info->historidac)] | PFMR_CLOBATHINC_SECON
  return segtable;
}
```

Trained on linux source code

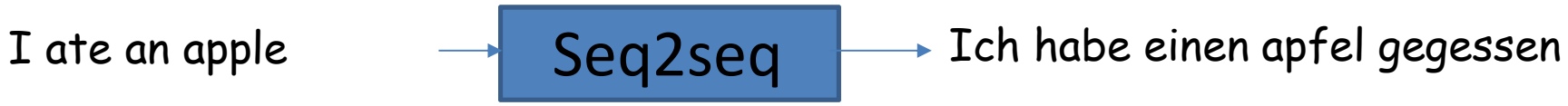
Actually uses a *character-level* model (predicts character sequences)

Composing music with RNN



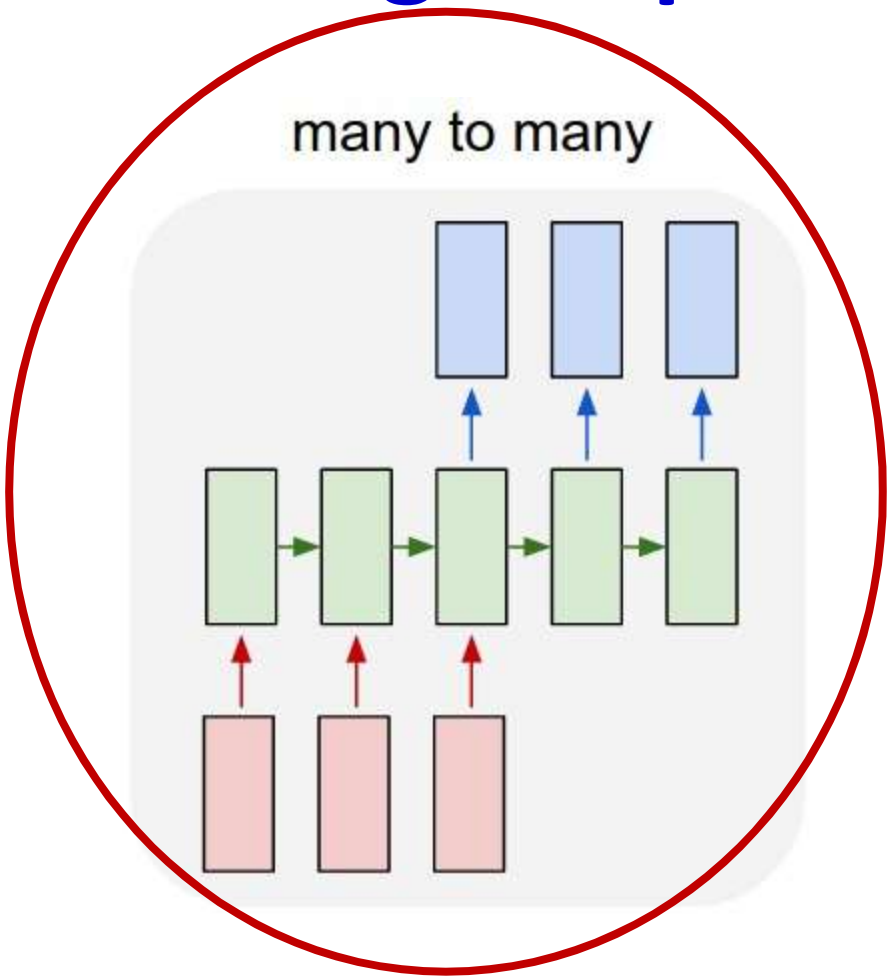
http://www.hexahedria.com/2015/08/03/composing-music-with-recurrent-neural-networks/

Returning our problem



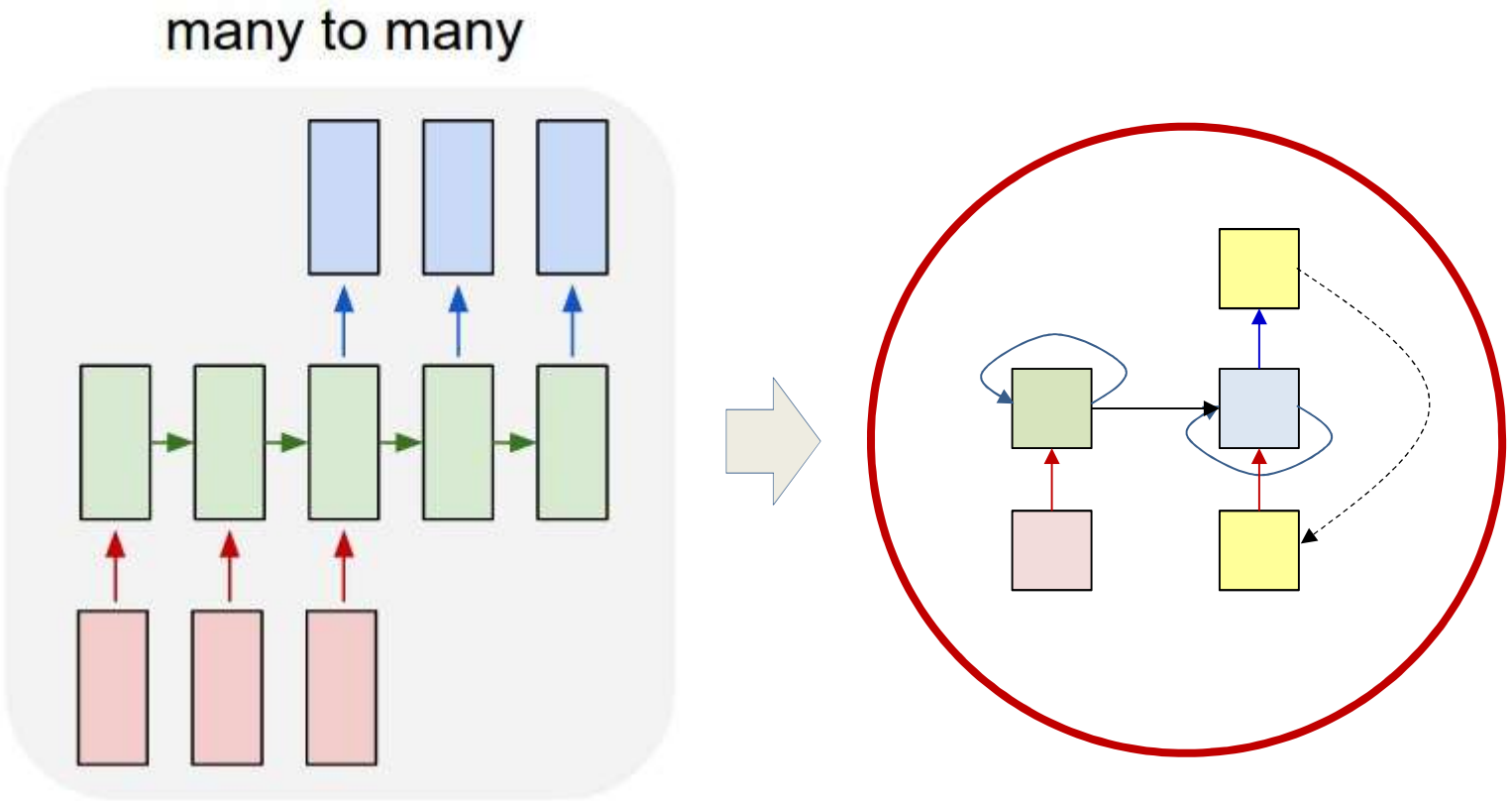
- Problem:
  - A sequence $X_1 \ldots X_N$ goes in
  - A different sequence $Y_1 \ldots Y_M$ comes out
- Similar to predicting text, but with a difference
  - The output is in a different language..

Modelling the problem



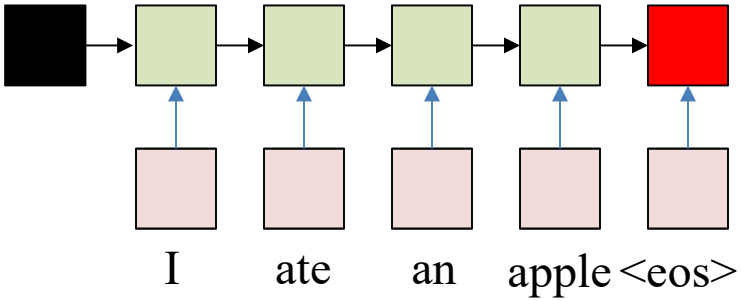
- *Delayed* sequence to sequence

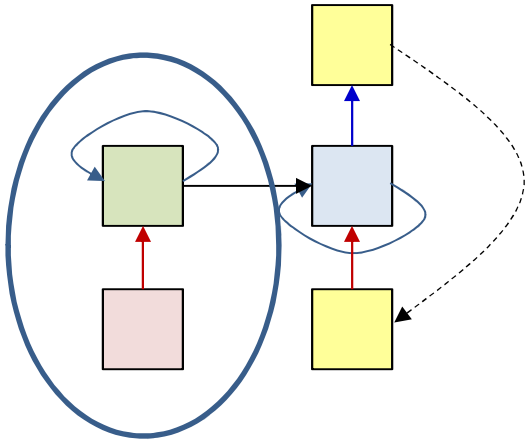
Modelling the problem



- *Delayed* sequence to sequence
  - Delayed *self-referencing* sequence-to-sequence

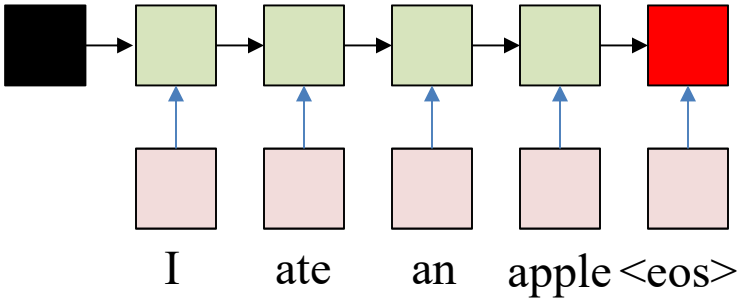
The “simple” translation model

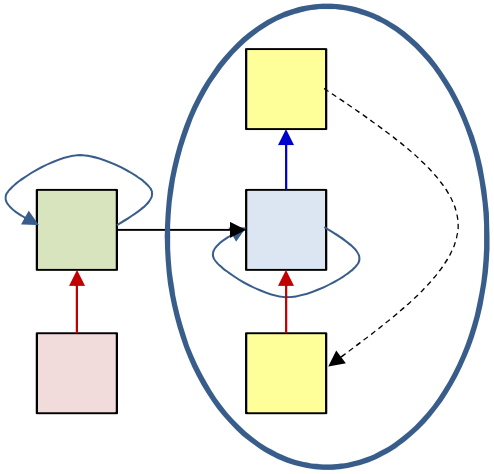




- The input sequence feeds into an recurrent structure
- The input sequence is terminated by an explicit <eos> symbol
  - The hidden activation at the <eos> “stores” all information about the sentence

The “simple” translation model

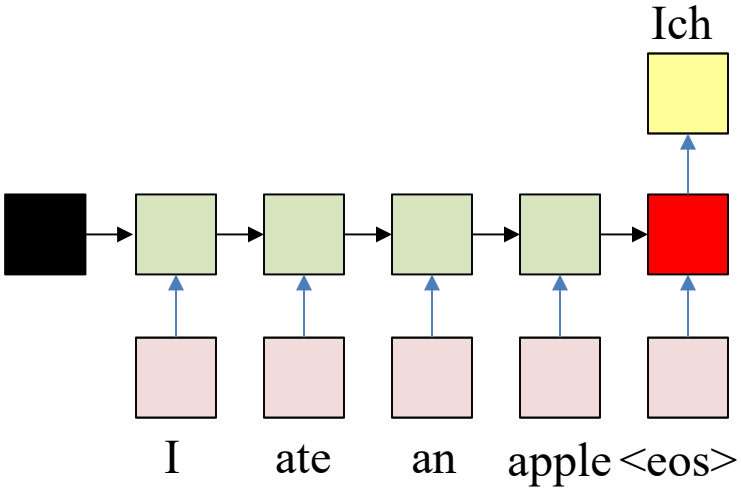




- The input sequence feeds into an recurrent structure
- The input sequence is terminated by an explicit <eos> symbol
  - The hidden activation at the <eos> “stores” all information about the sentence

- Subsequently a *second* RNN uses the hidden activation as initial state to produce a sequence of outputs
  - The output at each time becomes the input at the next time
  - Output production continues until an <eos> is produced

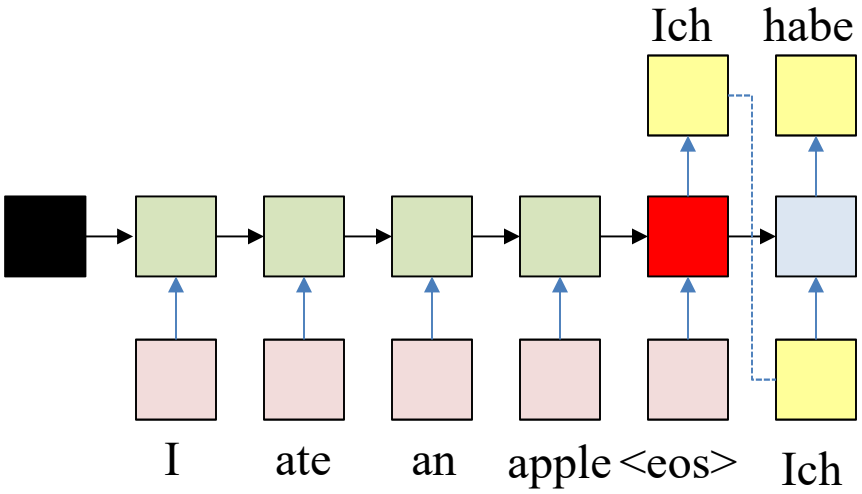
The “simple” translation model



- The input sequence feeds into an recurrent structure
- The input sequence is terminated by an explicit <eos> symbol
  - The hidden activation at the <eos> “stores” all information about the sentence

- Subsequently a *second* RNN uses the hidden activation as initial state to produce a sequence of outputs
  - The output at each time becomes the input at the next time
  - Output production continues until an <eos> is produced

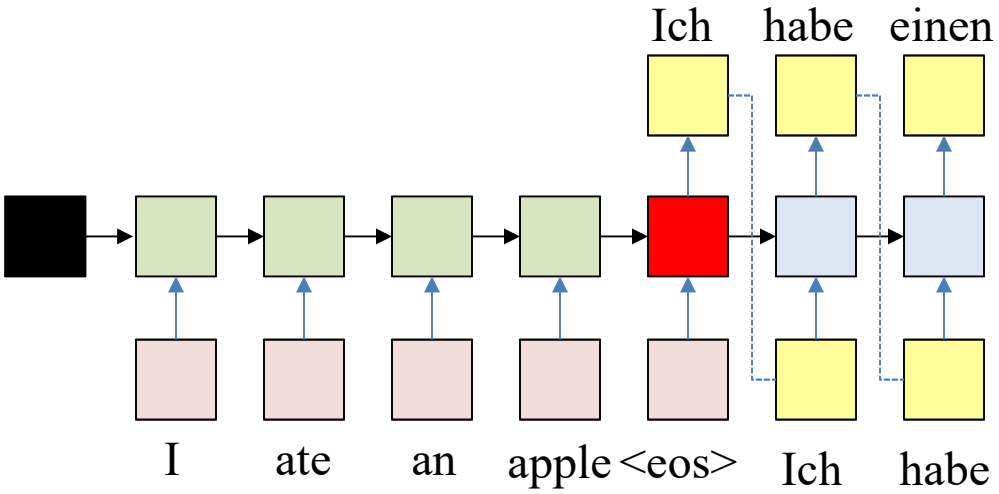
The “simple” translation model



- The input sequence feeds into an recurrent structure
- The input sequence is terminated by an explicit <eos> symbol
  - The hidden activation at the <eos> “stores” all information about the sentence

- Subsequently a *second* RNN uses the hidden activation as initial state to produce a sequence of outputs
  - The output at each time becomes the input at the next time
  - Output production continues until an <eos> is produced

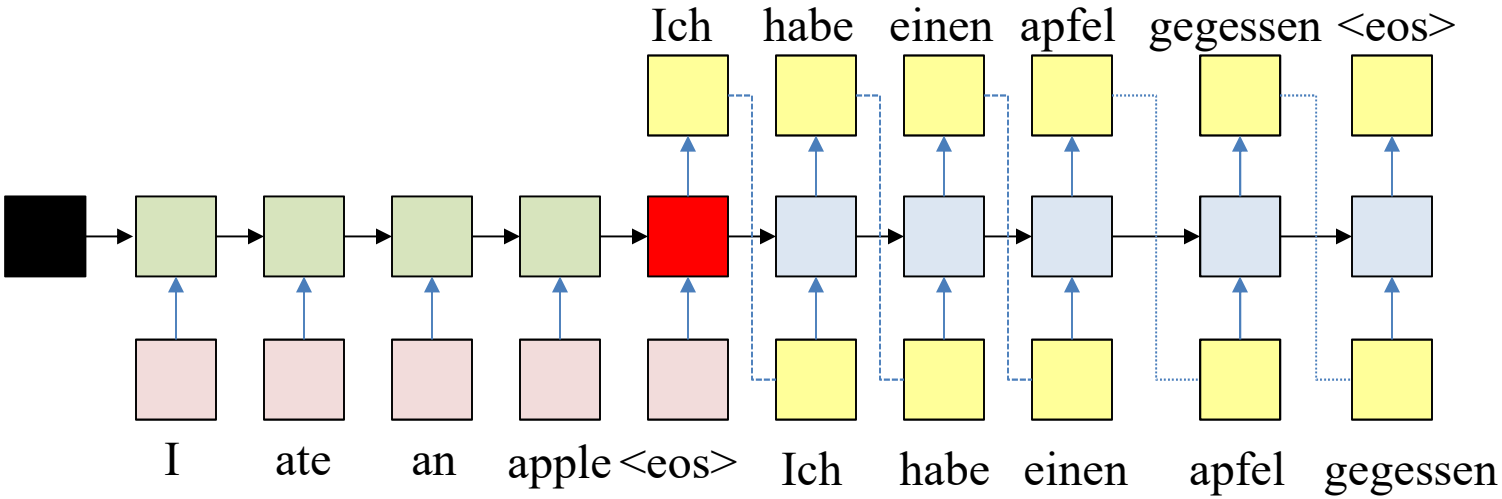
The “simple” translation model



- The input sequence feeds into an recurrent structure
- The input sequence is terminated by an explicit <eos> symbol
  - The hidden activation at the <eos> “stores” all information about the sentence

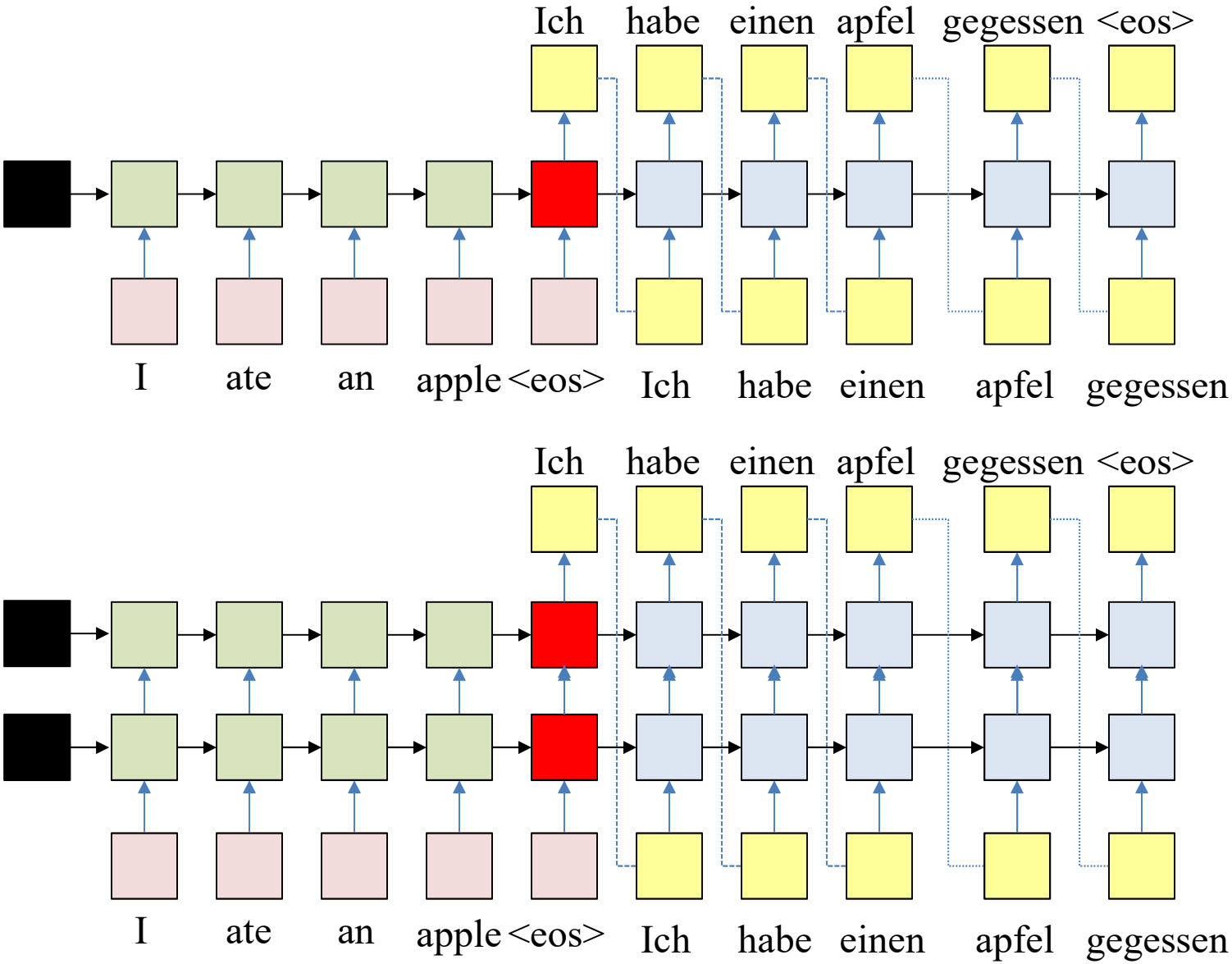
- Subsequently a *second* RNN uses the hidden activation as initial state to produce a sequence of outputs
  - The output at each time becomes the input at the next time
  - Output production continues until an <eos> is produced

The “simple” translation model



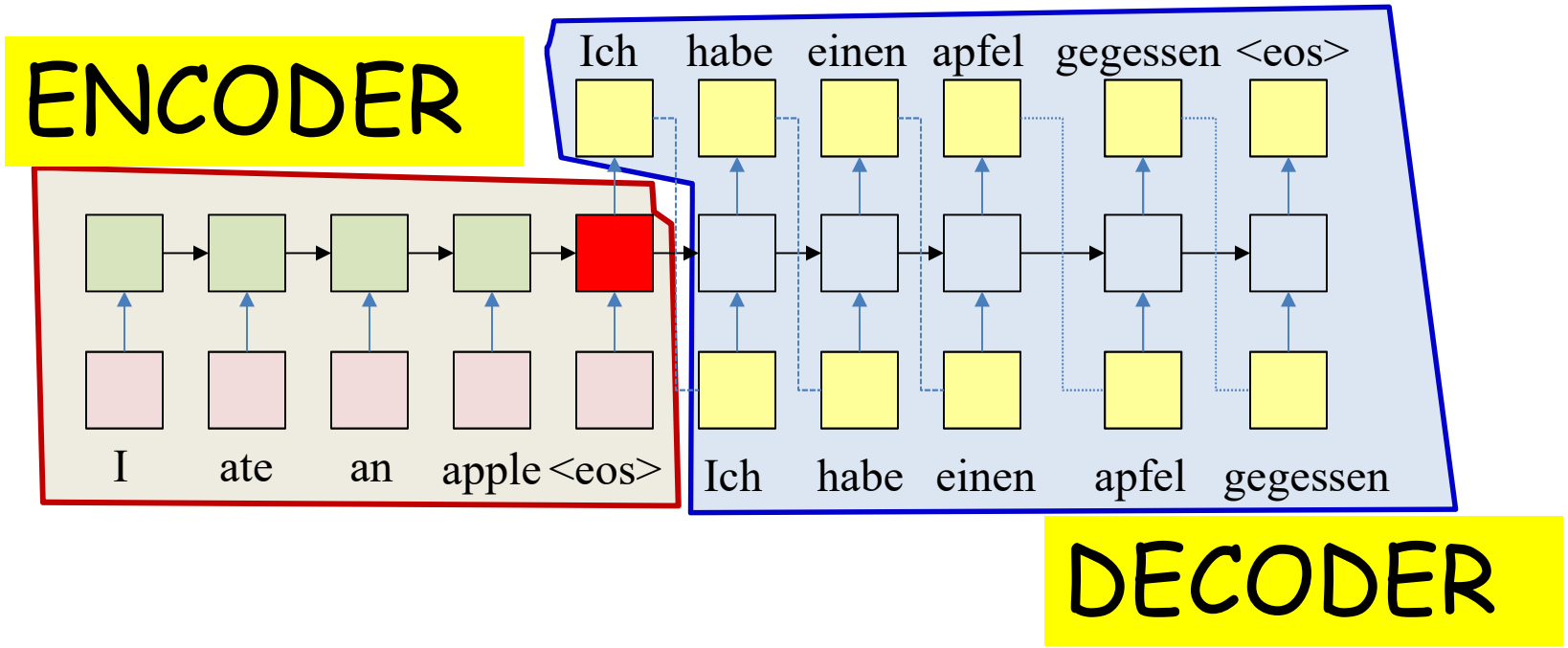
- The input sequence feeds into an recurrent structure
- The input sequence is terminated by an explicit <eos> symbol
  - The hidden activation at the <eos> “stores” all information about the sentence

- Subsequently a *second* RNN uses the hidden activation as initial state to produce a sequence of outputs
  - The output at each time becomes the input at the next time
  - Output production continues until an <eos> is produced



- We will illustrate with a single hidden layer, but the discussion generalizes to more layers

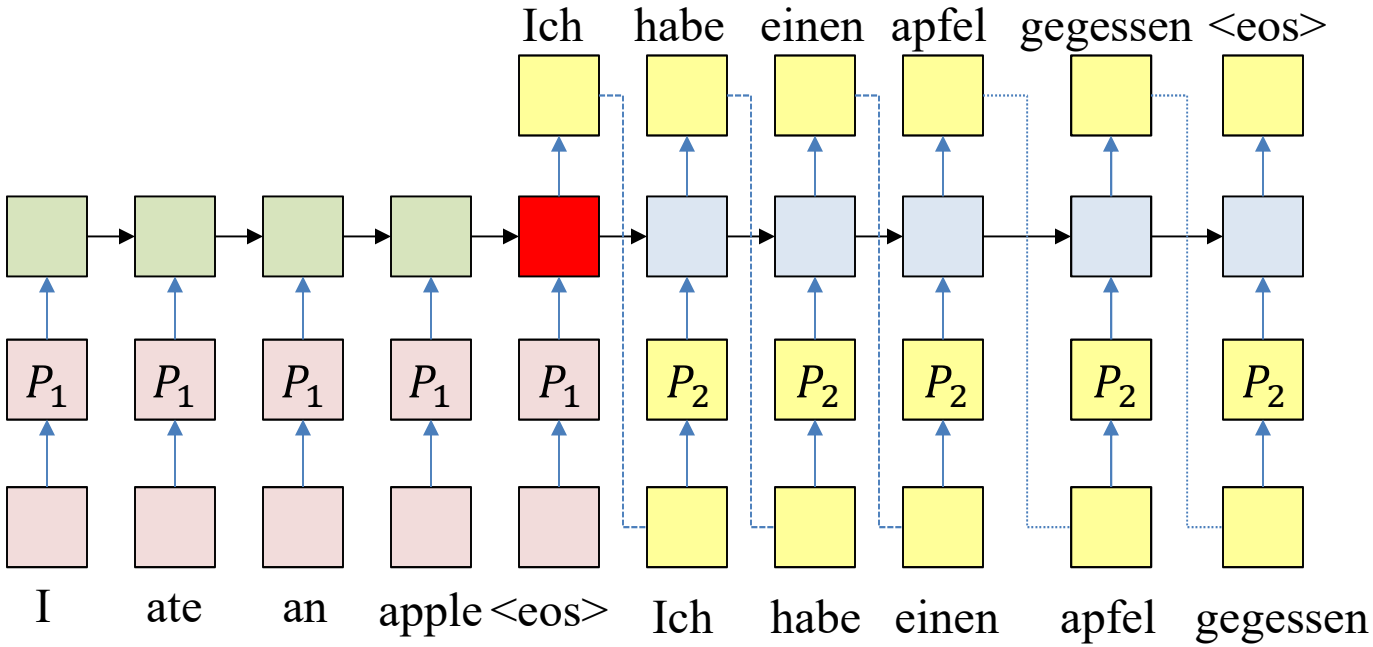
The "simple" translation model



- The input sequence feeds into an recurrent structure
- The input sequence is terminated by an explicit <eos> symbol
  - The hidden activation at the <eos> "stores" all information about the sentence

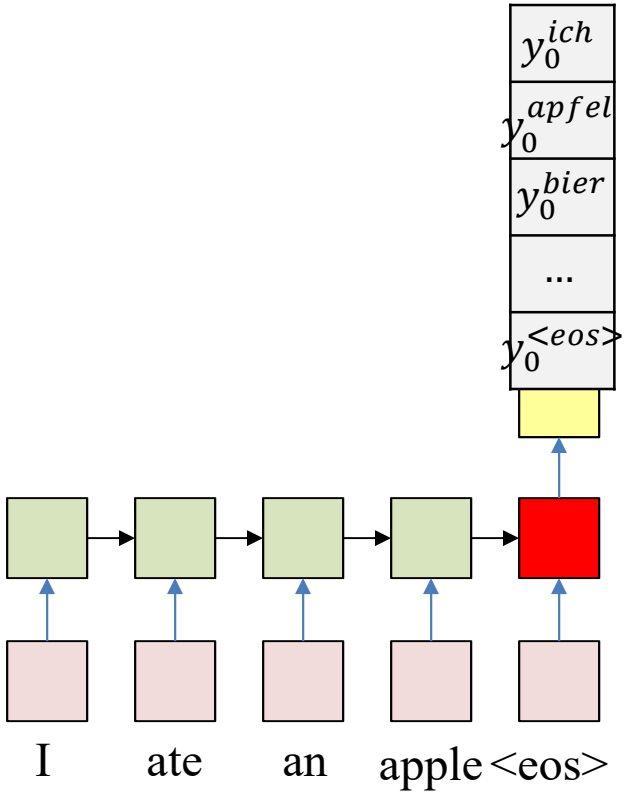
- Subsequently a *second* RNN uses the hidden activation as initial state to produce a sequence of outputs
  - The output at each time becomes the input at the next time
  - Output production continues until an <eos> is produced

The “simple” translation model



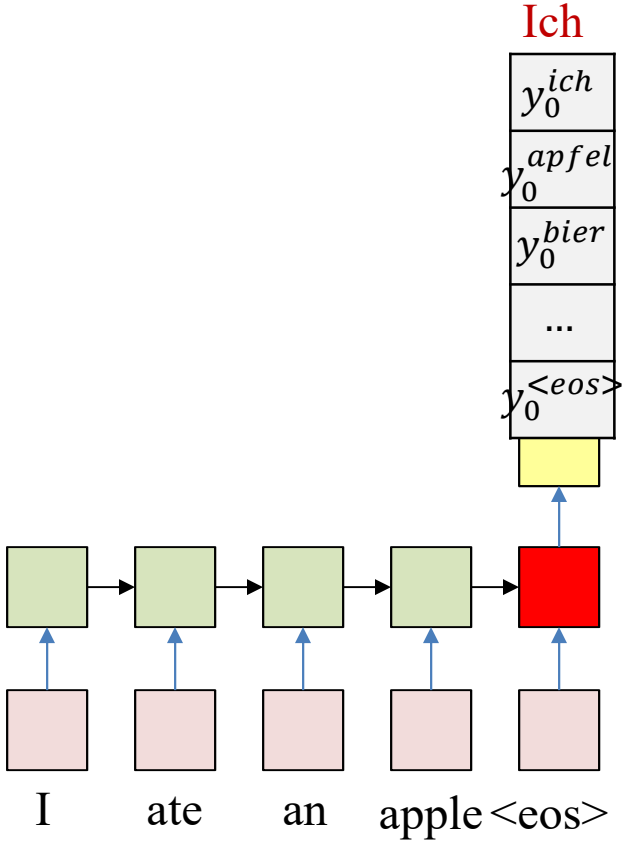
- A more detailed look: The one-hot word representations may be compressed via embeddings
  - Embeddings will be learned along with the rest of the net
  - In the following slides we will not represent the projection matrices

What the network actually produces



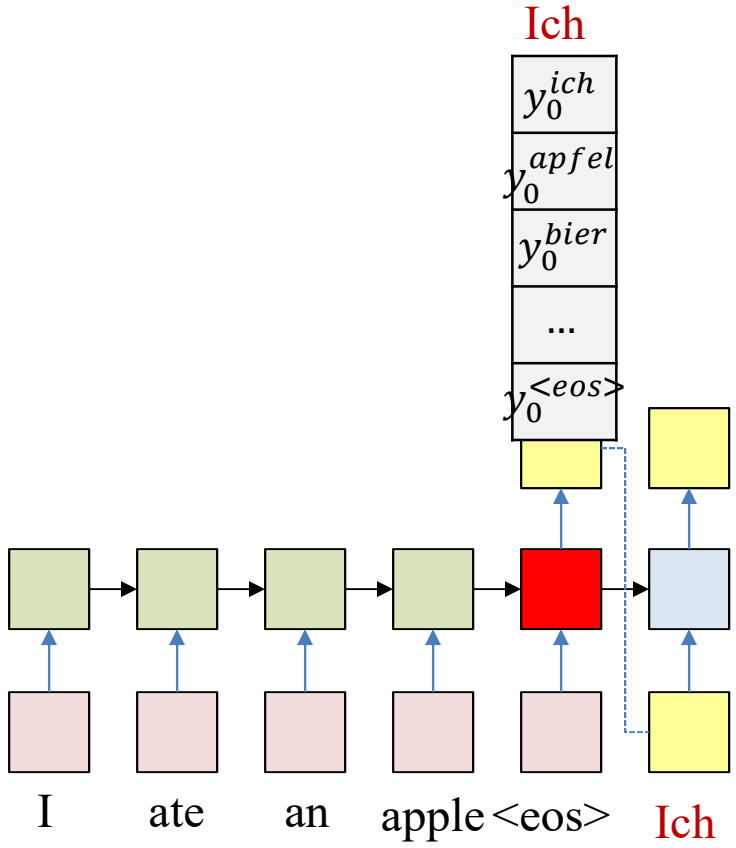
- At each time k the network actually produces a probability distribution over the output vocabulary
  - $y_k^w = P(O_k = w | O_{k-1}, \dots, O_1, I_1, \dots, I_N)$
  - The probability given the entire input sequence $I_1, \dots, I_N$ and the partial output sequence $O_1, \dots, O_{k-1}$ until k
- At each time a word is *drawn* from the output distribution
- The drawn word is provided as input to the next time

What the network actually produces



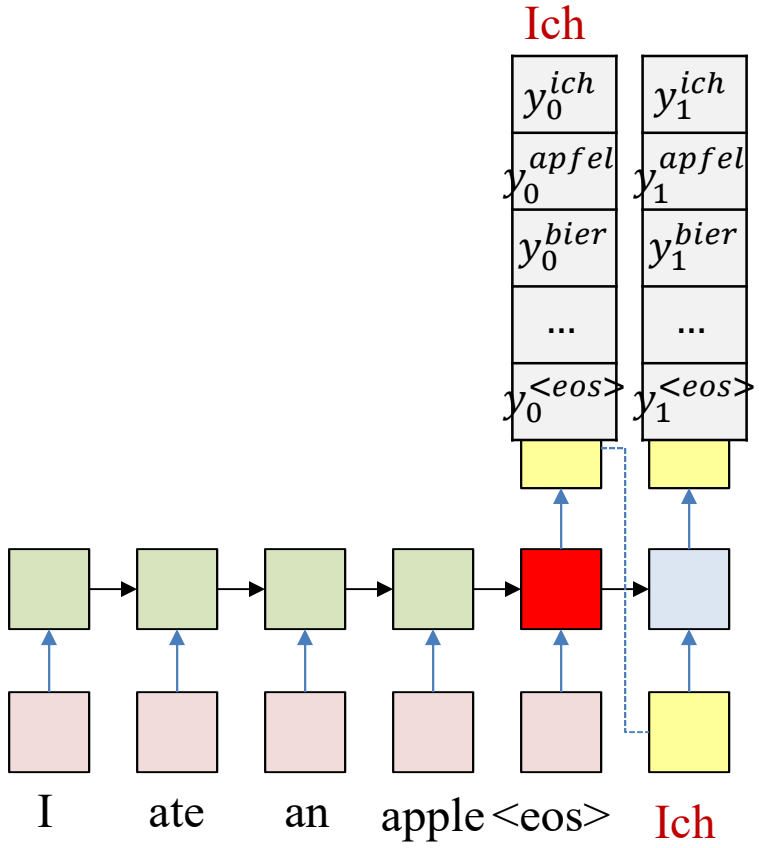
- At each time k the network actually produces a probability distribution over the output vocabulary
  - $y_k^w = P(O_k = w | O_{k-1}, \dots, O_1, I_1, \dots, I_N)$
  - The probability given the entire input sequence $I_1, \dots, I_N$ and the partial output sequence $O_1, \dots, O_{k-1}$ until k
- At each time a word is *drawn* from the output distribution
- The drawn word is provided as input to the next time

What the network actually produces



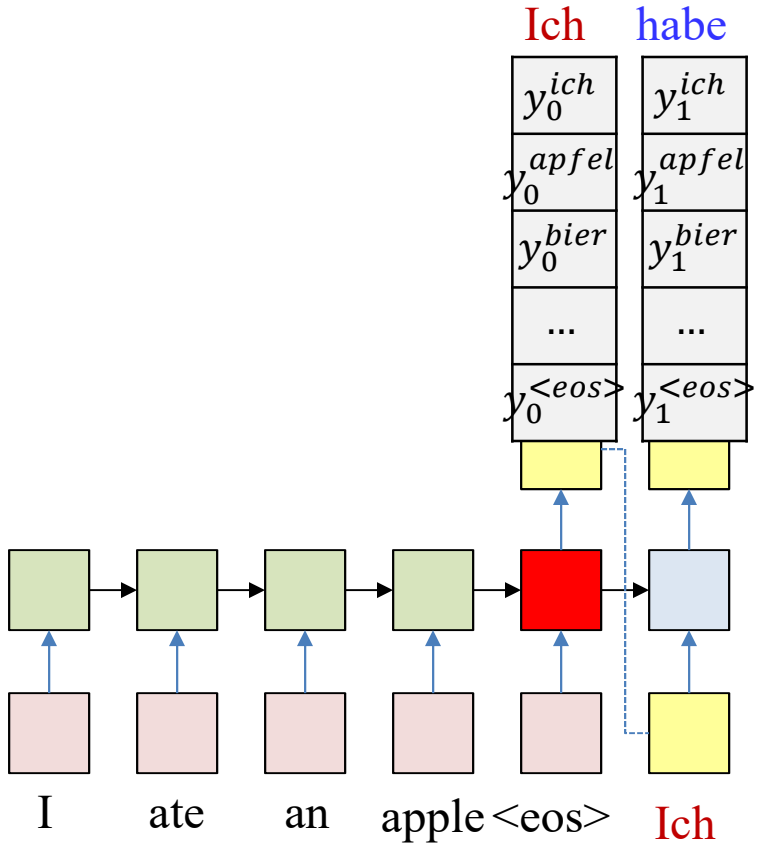
- At each time k the network actually produces a probability distribution over the output vocabulary
  - $y_k^w = P(O_k = w | O_{k-1}, \dots, O_1, I_1, \dots, I_N)$
  - The probability given the entire input sequence $I_1, \dots, I_N$ and the partial output sequence $O_1, \dots, O_{k-1}$ until k
- At each time a word is *drawn* from the output distribution
- The drawn word is provided as input to the next time

What the network actually produces



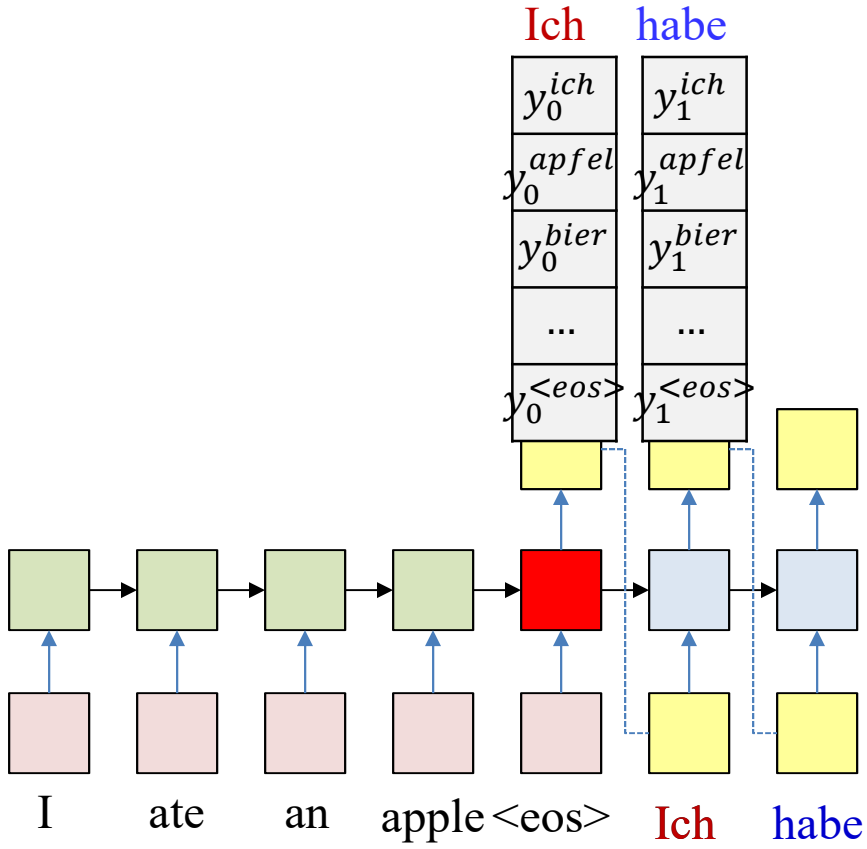
- At each time k the network actually produces a probability distribution over the output vocabulary
  - $y_k^w = P(O_k = w | O_{k-1}, \dots, O_1, I_1, \dots, I_N)$
  - The probability given the entire input sequence $I_1, \dots, I_N$ and the partial output sequence $O_1, \dots, O_{k-1}$ until k
- At each time a word is *drawn* from the output distribution
- The drawn word is provided as input to the next time

What the network actually produces



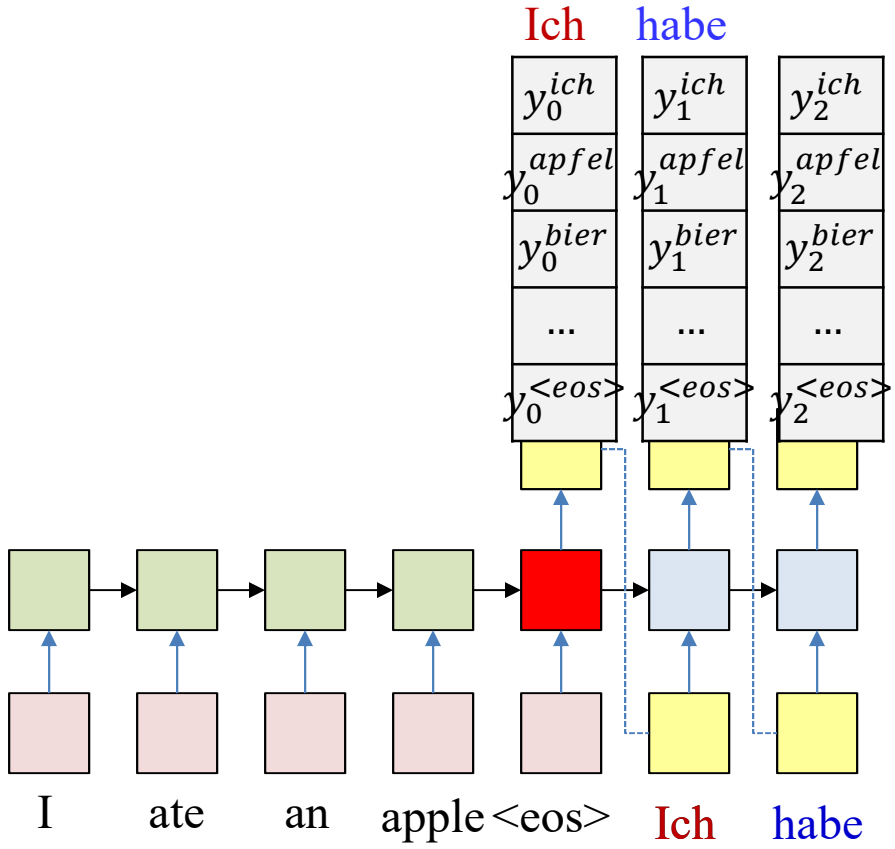
- At each time k the network actually produces a probability distribution over the output vocabulary
  - $y_k^w = P(O_k = w | O_{k-1}, \dots, O_1, I_1, \dots, I_N)$
  - The probability given the entire input sequence $I_1, \dots, I_N$ and the partial output sequence $O_1, \dots, O_{k-1}$ until k
- At each time a word is *drawn* from the output distribution
- The drawn word is provided as input to the next time

What the network actually produces



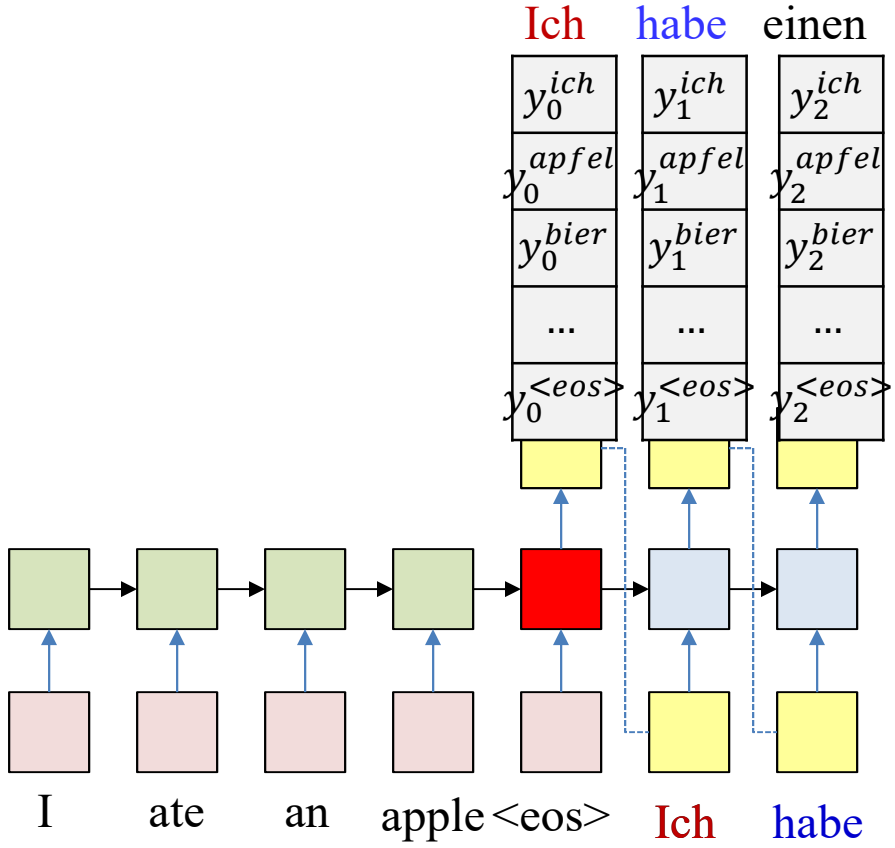
- At each time k the network actually produces a probability distribution over the output vocabulary
  - $y_k^w = P(O_k = w | O_{k-1}, \dots, O_1, I_1, \dots, I_N)$
  - The probability given the entire input sequence $I_1, \dots, I_N$ and the partial output sequence $O_1, \dots, O_{k-1}$ until k
- At each time a word is *drawn* from the output distribution
- The drawn word is provided as input to the next time

What the network actually produces



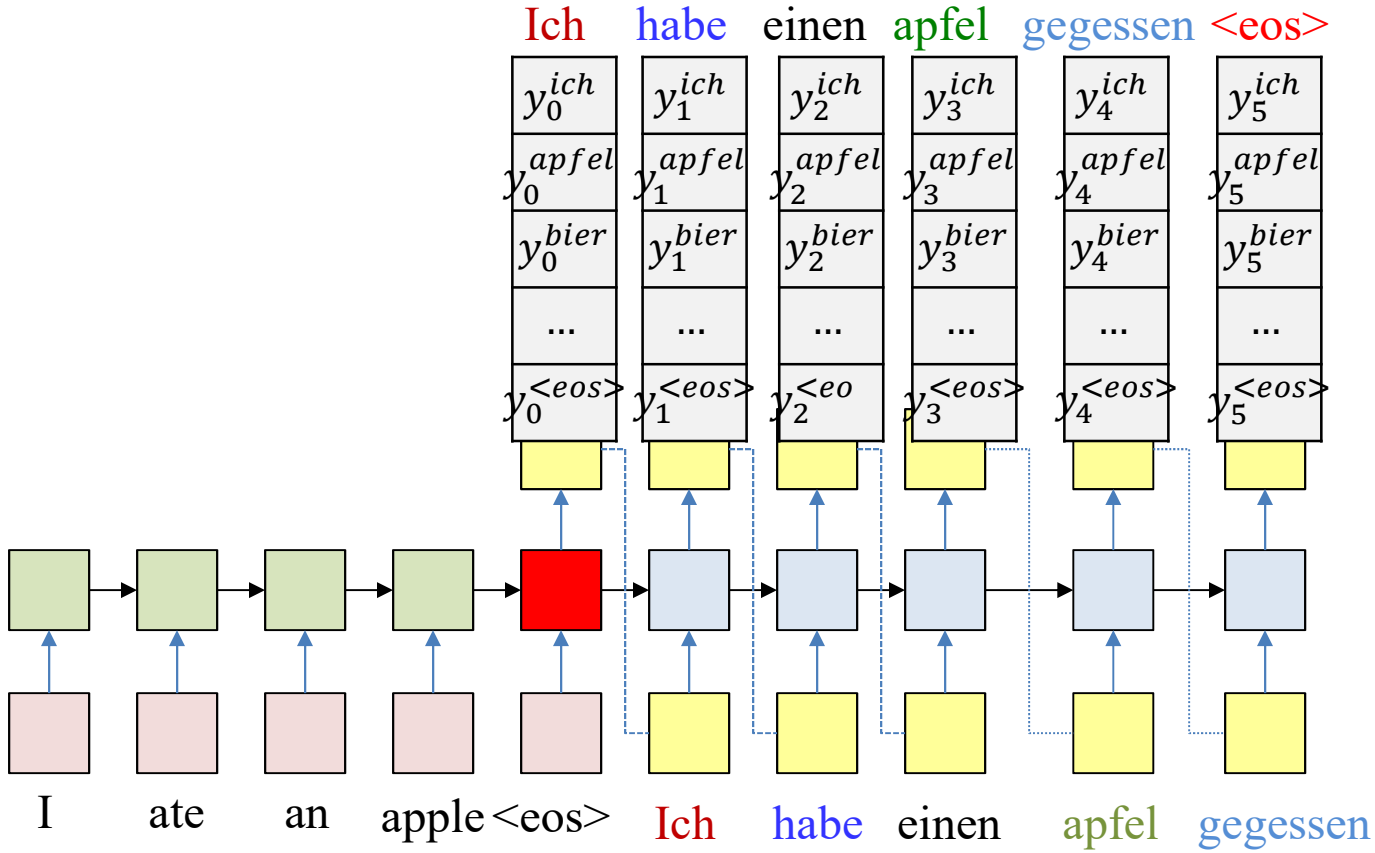
- At each time k the network actually produces a probability distribution over the output vocabulary
  - $y_k^w = P(O_k = w | O_{k-1}, \dots, O_1, I_1, \dots, I_N)$
  - The probability given the entire input sequence $I_1, \dots, I_N$ and the partial output sequence $O_1, \dots, O_{k-1}$ until k
- At each time a word is *drawn* from the output distribution
- The drawn word is provided as input to the next time

What the network actually produces



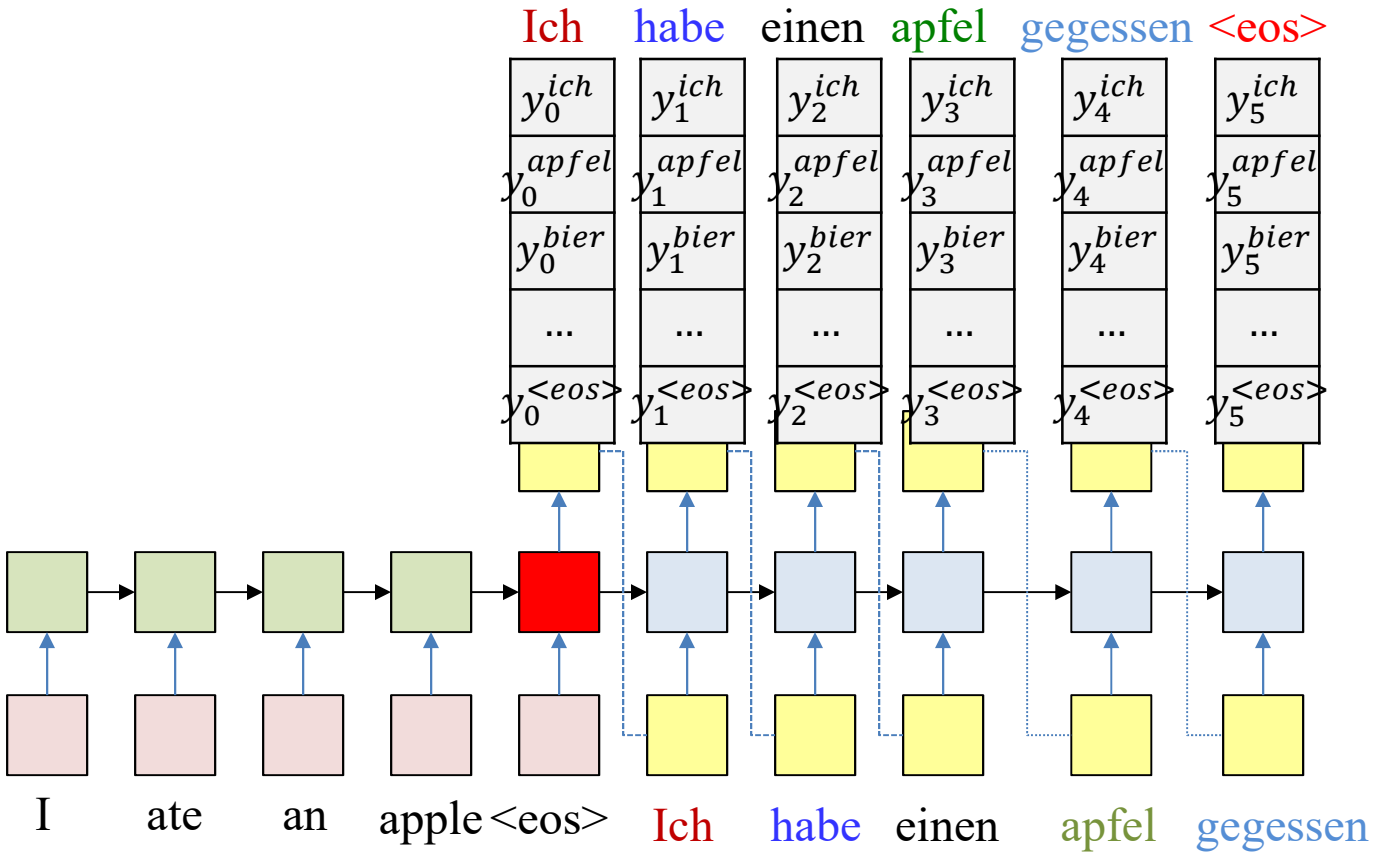
- At each time k the network actually produces a probability distribution over the output vocabulary
  - $y_k^w = P(O_k = w | O_{k-1}, \dots, O_1, I_1, \dots, I_N)$
  - The probability given the entire input sequence $I_1, \dots, I_N$ and the partial output sequence $O_1, \dots, O_{k-1}$ until k
- At each time a word is *drawn* from the output distribution
- The drawn word is provided as input to the next time

What the network actually produces



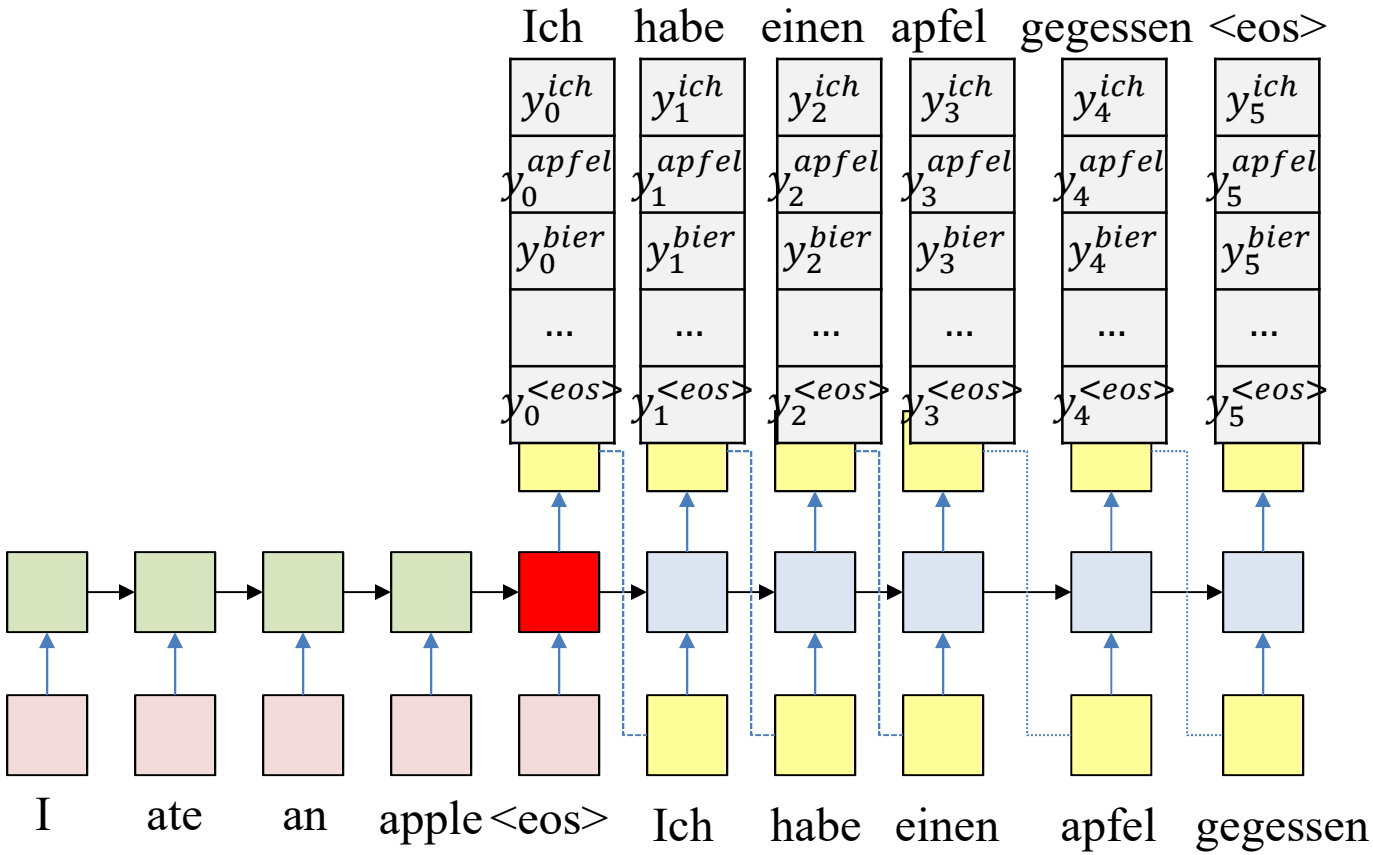
- At each time k the network actually produces a probability distribution over the output vocabulary
  - $y_k^w = P(O_k = w | O_{k-1}, \dots, O_1, I_1, \dots, I_N)$
  - The probability given the entire input sequence $I_1, \dots, I_N$ and the partial output sequence $O_1, \dots, O_{k-1}$ until k
- At each time a word is *drawn* from the output distribution
- The drawn word is provided as input to the next time

Generating an output from the net



- At each time the network produces a probability distribution over words, given the entire input and previous outputs
- At each time a word is *drawn* from the output distribution
- The drawn word is provided as input to the next time
- The process continues until an <eos> is generated

The probability of the output

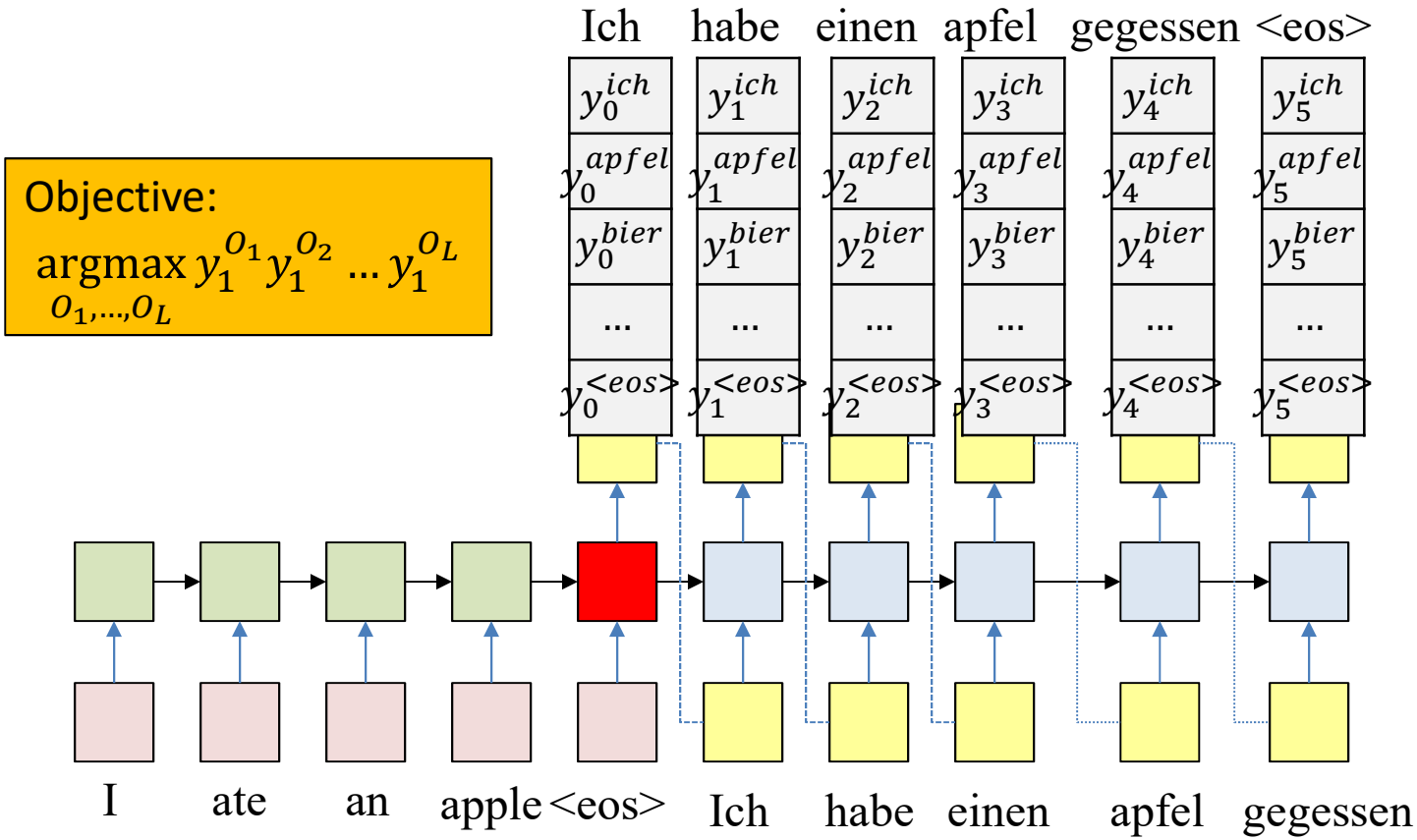


$$P(O_1, \dots, O_L | W_1^{in}, \dots, W_N^{in}) = y_1^{O_1} y_1^{O_2} \dots y_1^{O_L}$$

- The objective of drawing: Produce the most likely output (that ends in an <eos>)

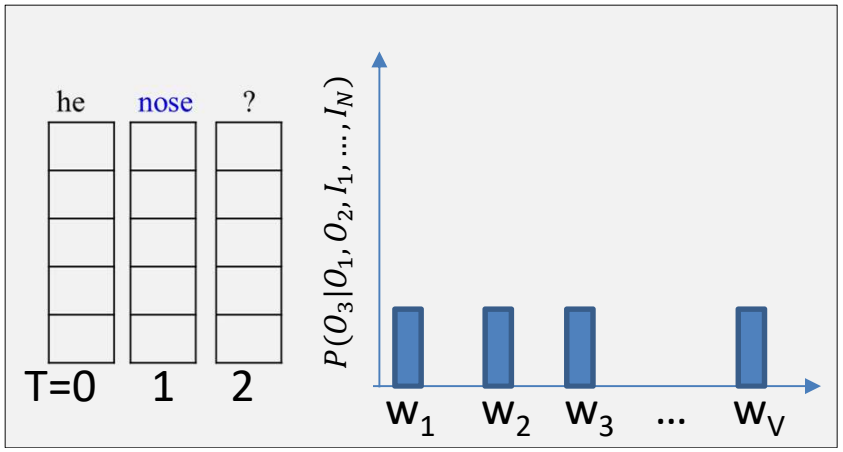
$$\underset{O_1,\dots,O_L}{\operatorname{argmax}} y_1^{O_1} y_1^{O_2} \dots y_1^{O_L}$$

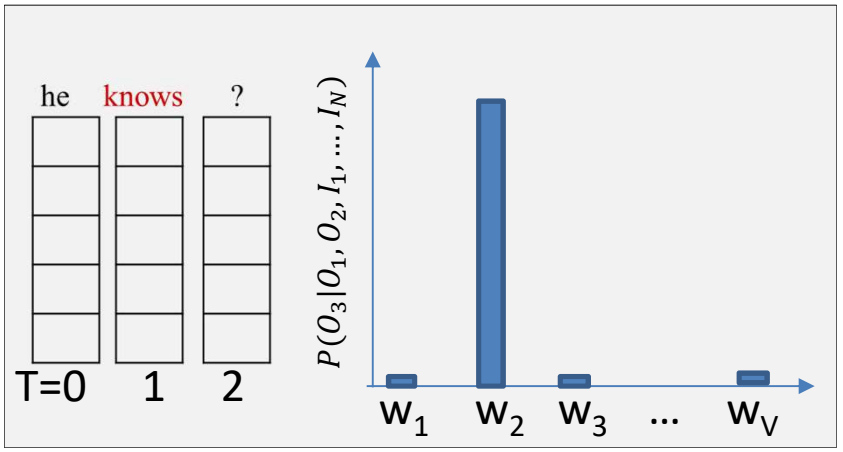
The probability of the output



- Cannot just pick the most likely symbol at each time
  - That may cause the distribution to be more "confused" at the next time
  - Choosing a different, less likely word could cause the distribution at the next time to be more peaky, resulting in a more likely output overall

Greedy is not good



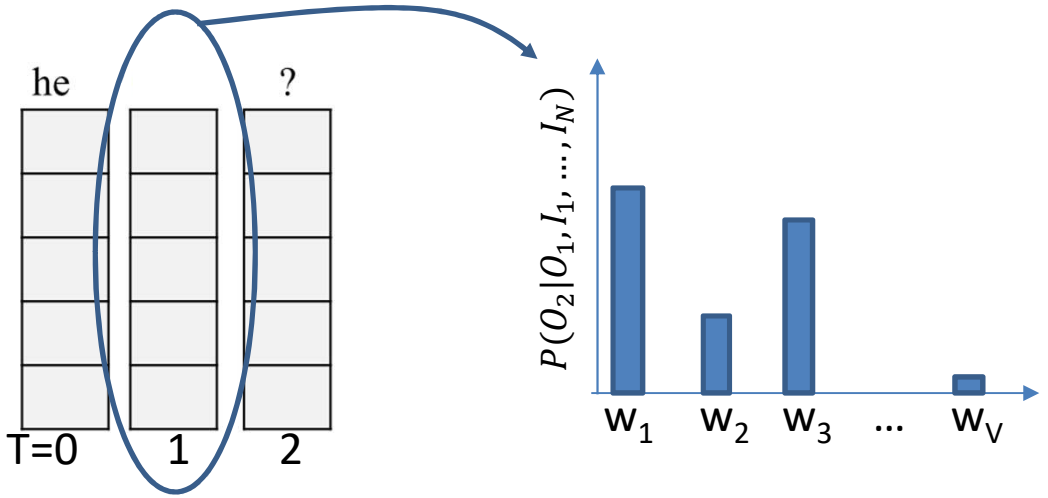


- Hypothetical example (from English speech recognition : Input is speech, output must be text)
- "Nose" has highest probability at t=2 and is selected
  - The model is very confused at t=3 and assigns low probabilities to many words at the next time
  - Selecting any of these will result in low probability for the entire 3-word sequence
- "Knows" has slightly lower probability than "nose", but is still high and is selected
  - "he knows" is a reasonable beginning and the model assigns high probabilities to words such as "something"
  - Selecting one of these results in higher overall probability for the 3-word sequence

Greedy is not good

What should we have chosen at t=2??

Will selecting "nose" continue to have a bad effect into the distant future?

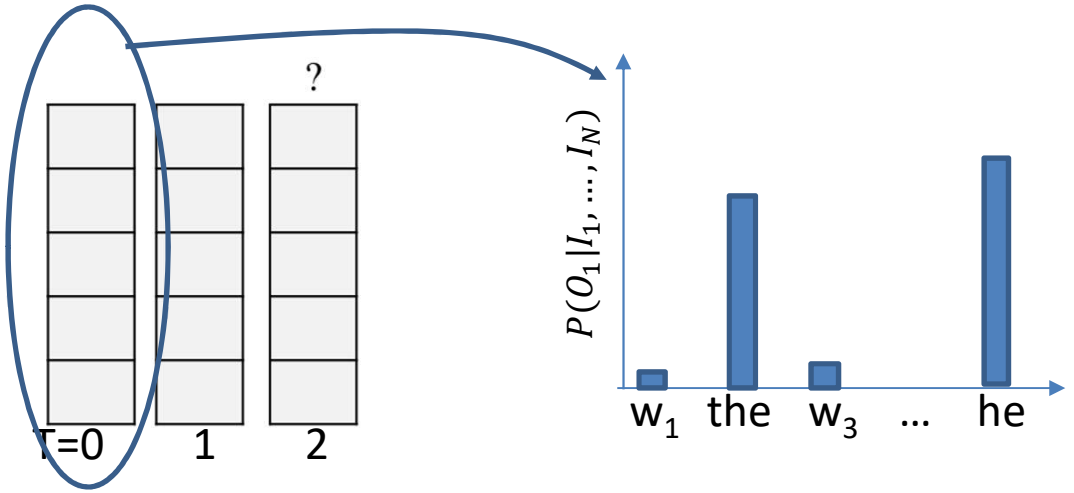


- Problem: Impossible to know a priori which word leads to the more promising future
  - Should we draw "nose" or "knows"?
  - Effect may not be obvious until several words down the line
  - Or the choice of the wrong word early may cumulatively lead to a poorer overall score over time

Greedy is not good

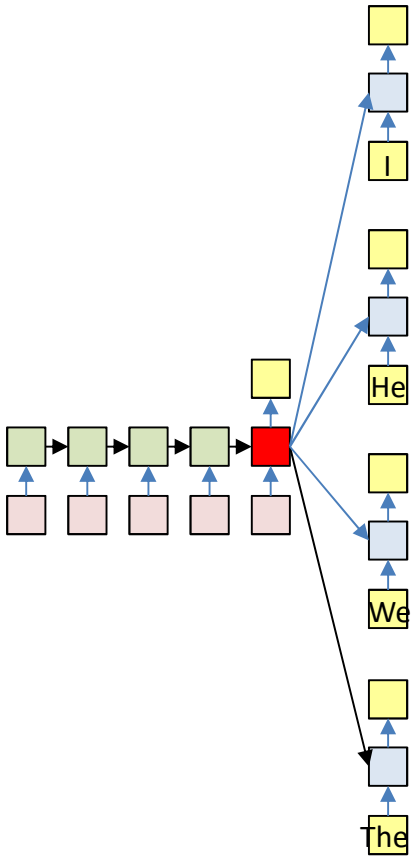
What should we have chosen at t=1??

Choose “the” or “he”?



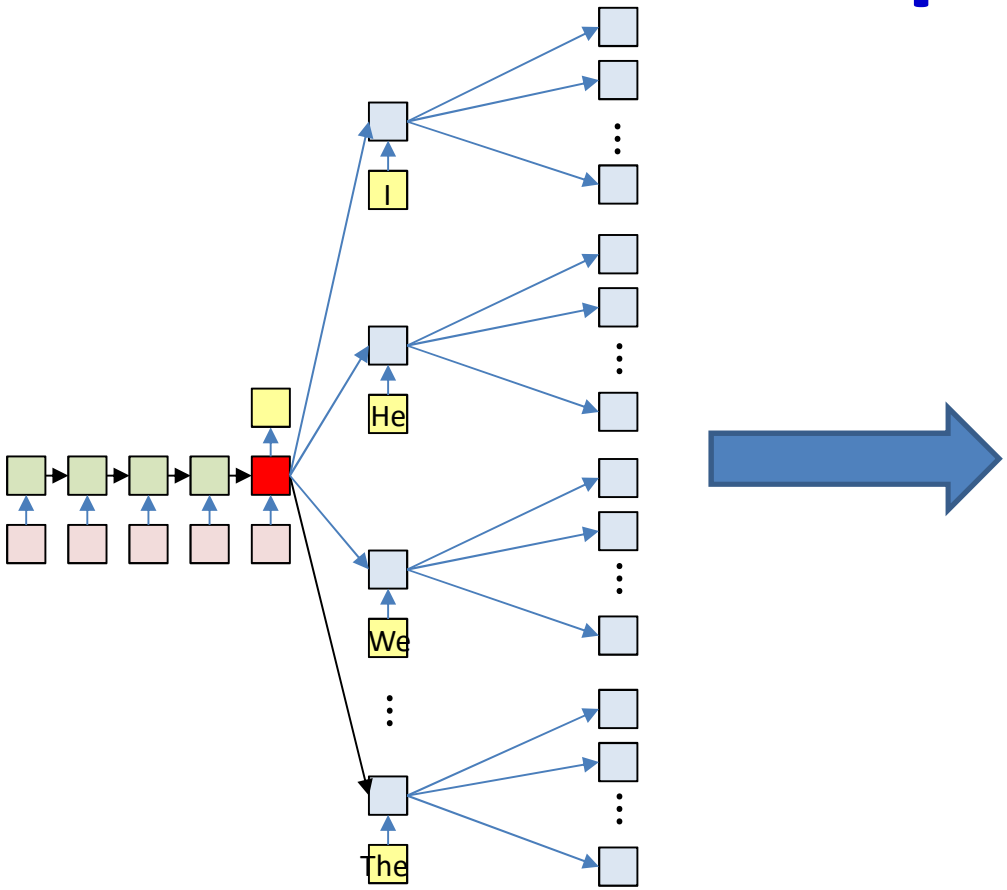
- Problem: Impossible to know a priori which word leads to the more promising future
  - Even earlier: Choosing the lower probability “the” instead of “he” at T=0 may have made a choice of “nose” more reasonable at T=1..
- In general, making a poor choice at any time commits us to a poor future
  - But we cannot know at that time the choice was poor
- Solution: Don’t choose..

Solution: Multiple choices



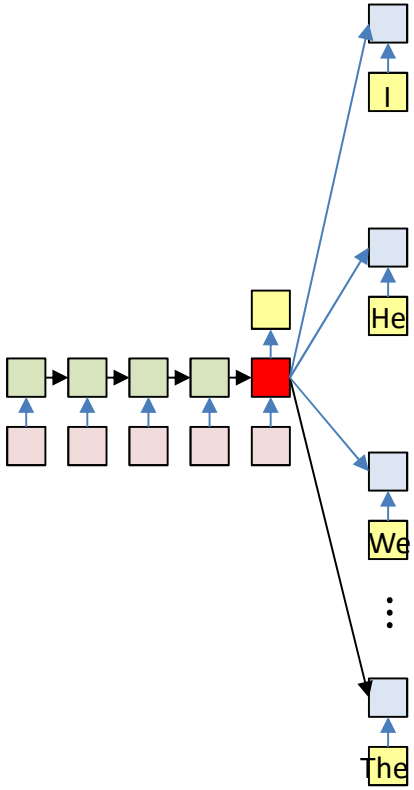
- Retain all choices and *fork* the network
  - With every possible word as input

Problem: Multiple choices



- **Problem**: This will blow up very quickly
  - For an output vocabulary of size V, after T output steps we'd have forked out V^T branches

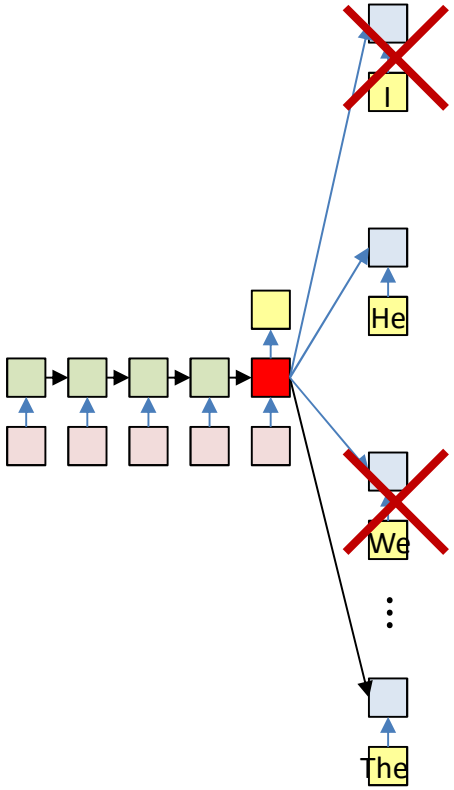
Solution: Prune



$$Top_K\ P(O_1|I_1, \ldots, I_N)$$

- **Solution: Prune**
  - At each time, retain only the top K scoring forks

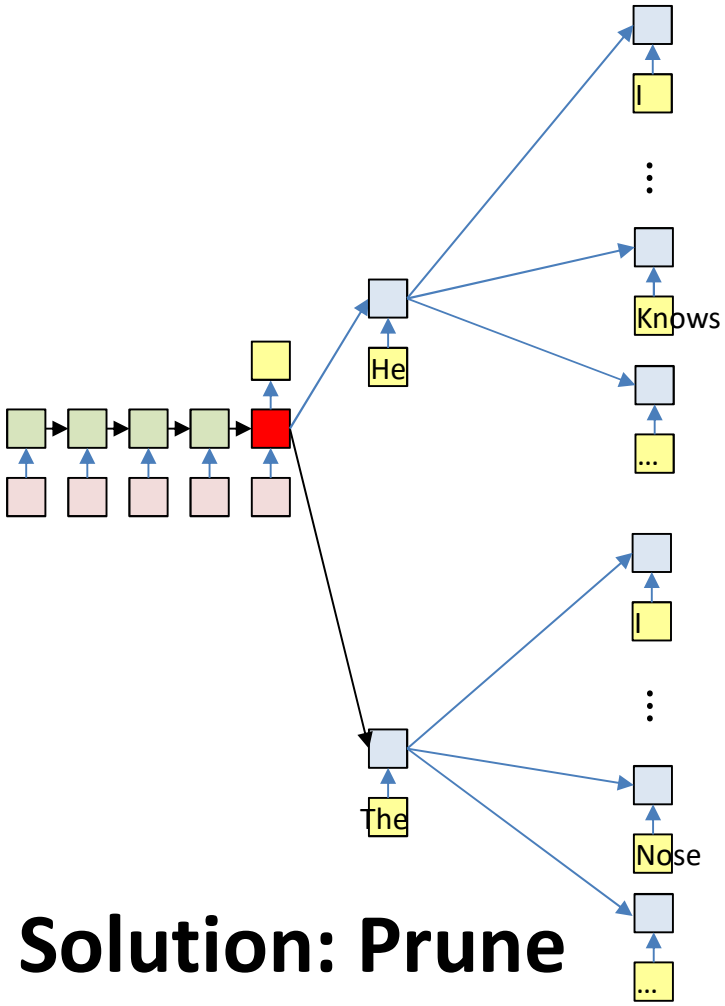
Solution: Prune



$$Top_K\ P(O_1|I_1, \ldots, I_N)$$

- **Solution: Prune**
  - At each time, retain only the top K scoring forks

Solution: Prune



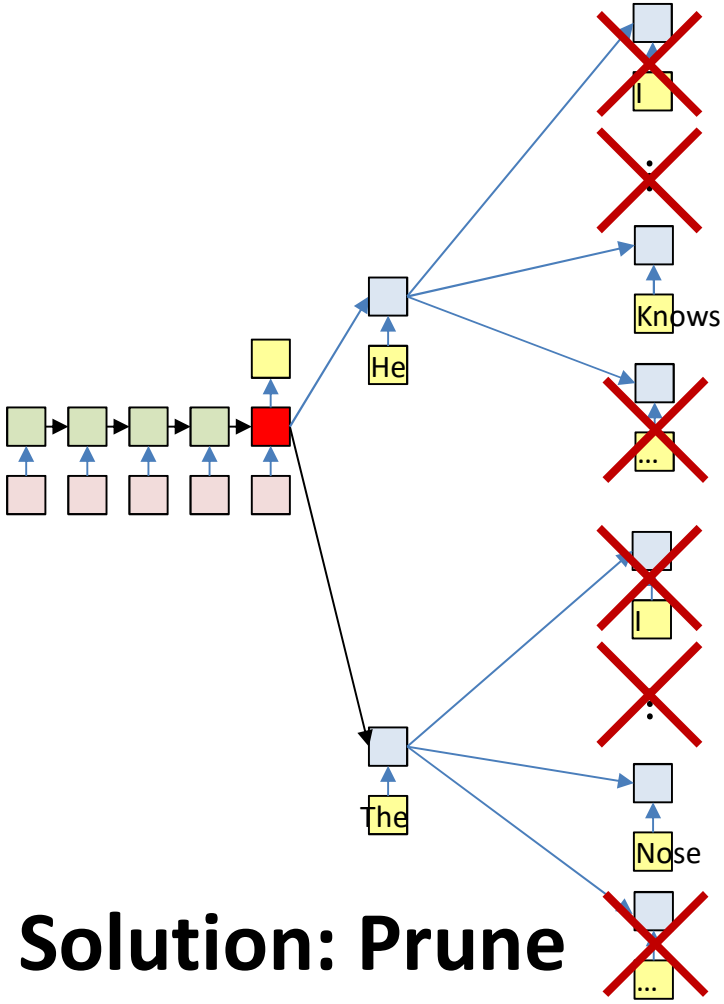
Note: based on product

$$Top_K\ P(O_2 O_1 | I_1, \ldots, I_N)$$

$$= Top_K\ P(O_2 | O_1, I_1, \ldots, I_N) P(O_1 | I_1, \ldots, I_N)$$

- **Solution: Prune**
  - At each time, retain only the top K scoring forks

Solution: Prune



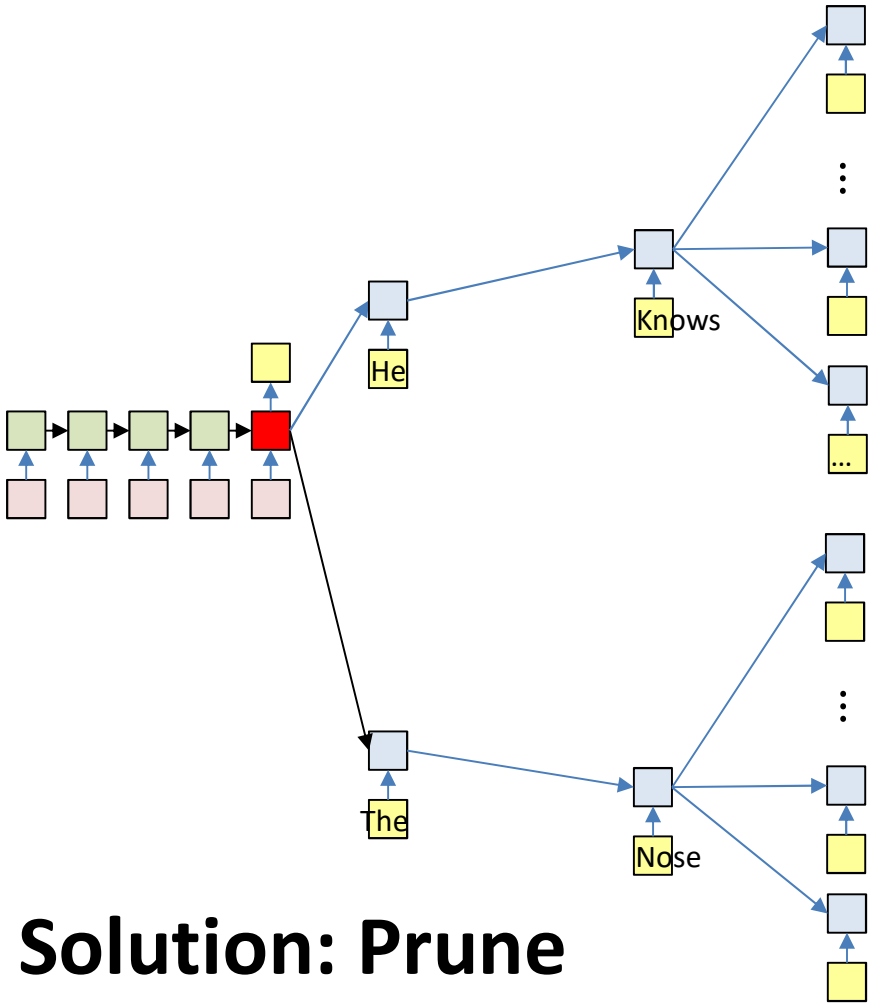
Note: based on product

$$Top_K\ P(O_2 O_1 | I_1, \ldots, I_N)$$

$$= Top_K\ P(O_2 | O_1, I_1, \ldots, I_N) P(O_1 | I_1, \ldots, I_N)$$

- **Solution: Prune**
  - At each time, retain only the top K scoring forks

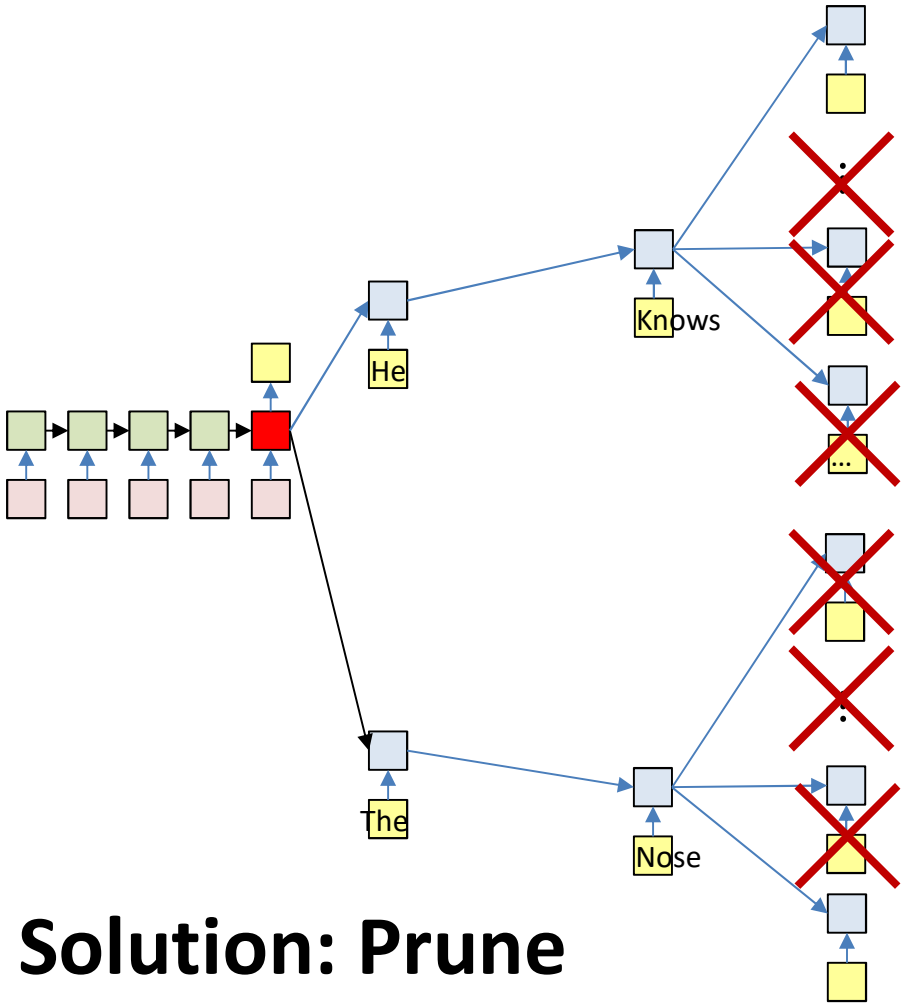
Solution: Prune



$$= Top_K P(O_2|O_1, I_1, \ldots, I_N) \times P(O_2|O_1, I_1, \ldots, I_N) \times P(O_1|I_1, \ldots, I_N)$$

- **Solution: Prune**
  - At each time, retain only the top K scoring forks

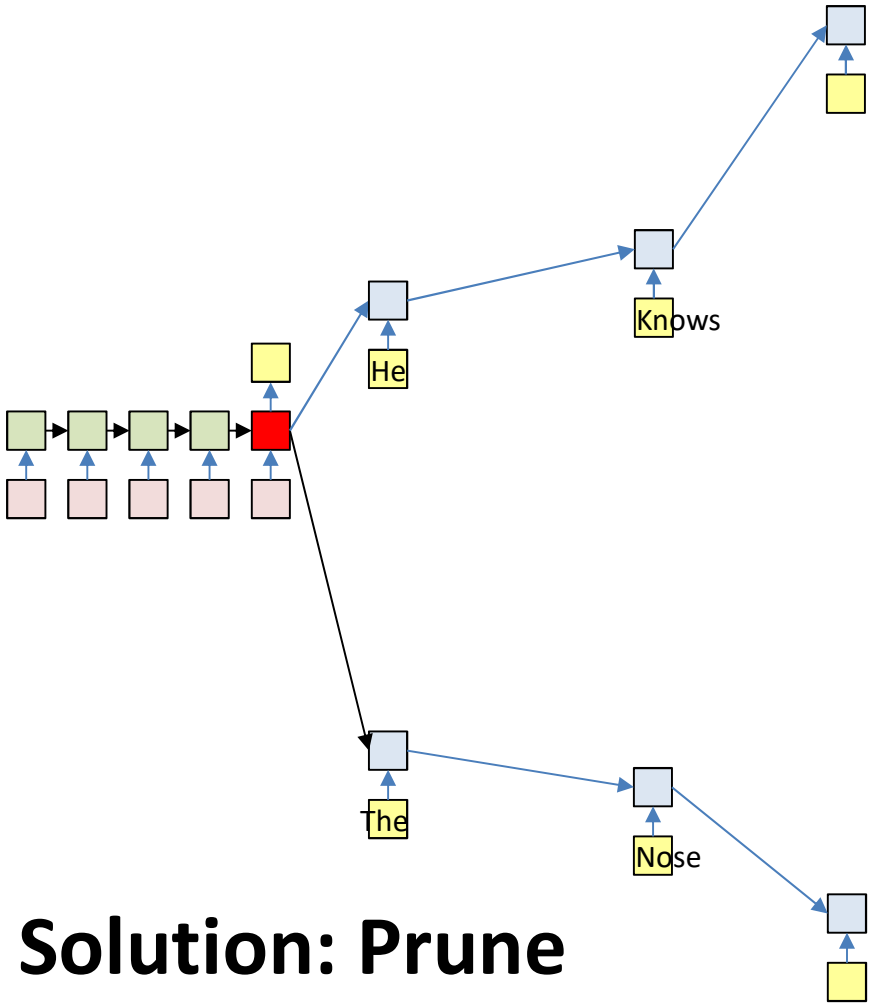
Solution: Prune



$$= Top_K P(O_2|O_1, I_1, \ldots, I_N) \times P(O_2|O_1, I_1, \ldots, I_N) \times P(O_1|I_1, \ldots, I_N)$$

- **Solution: Prune**
  - At each time, retain only the top K scoring forks

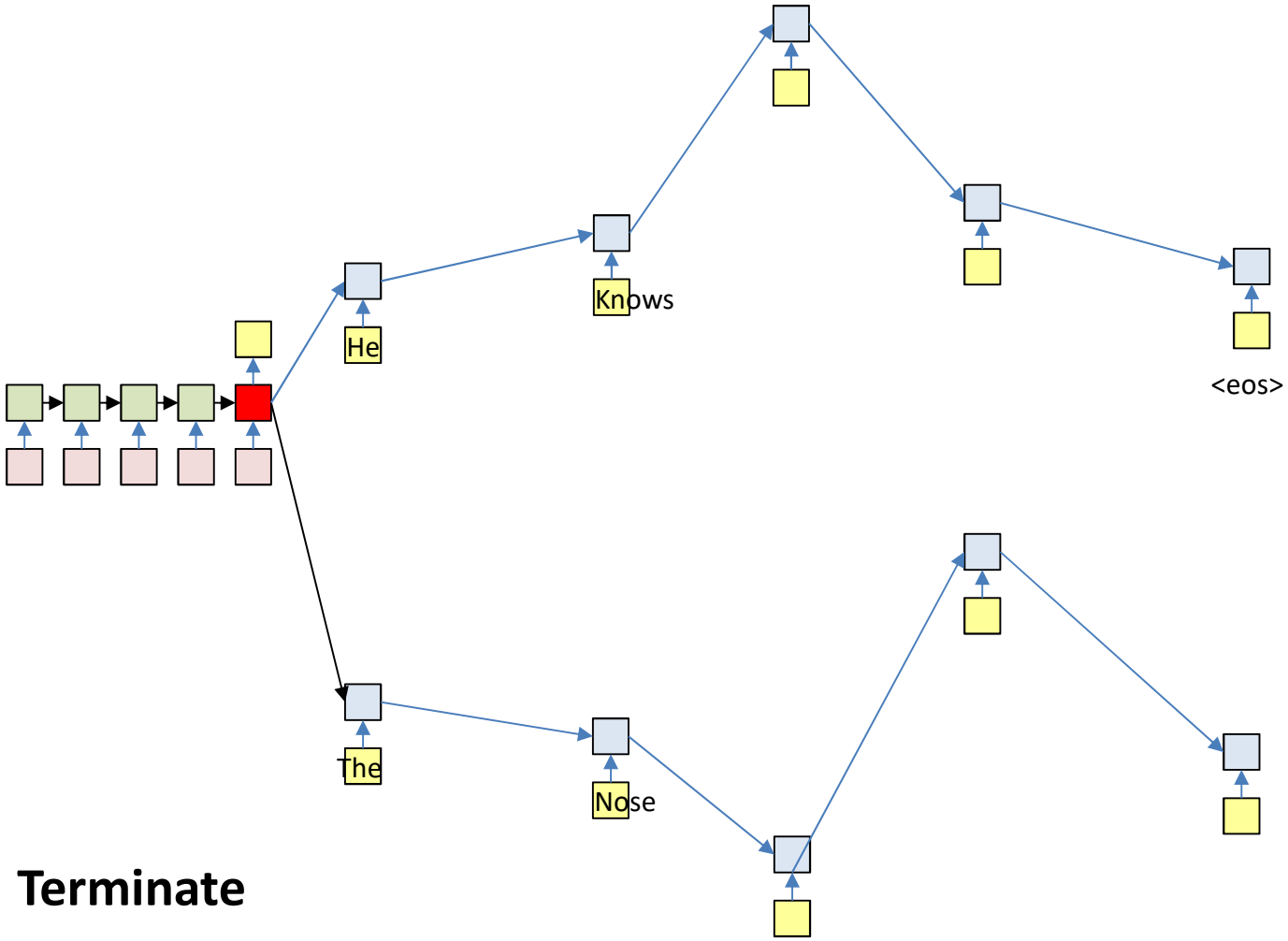
Solution: Prune



$$Top_K \prod_{t=1}^{n} P(O_n|O_1, \ldots, O_{n-1}, I_1, \ldots, I_N)$$

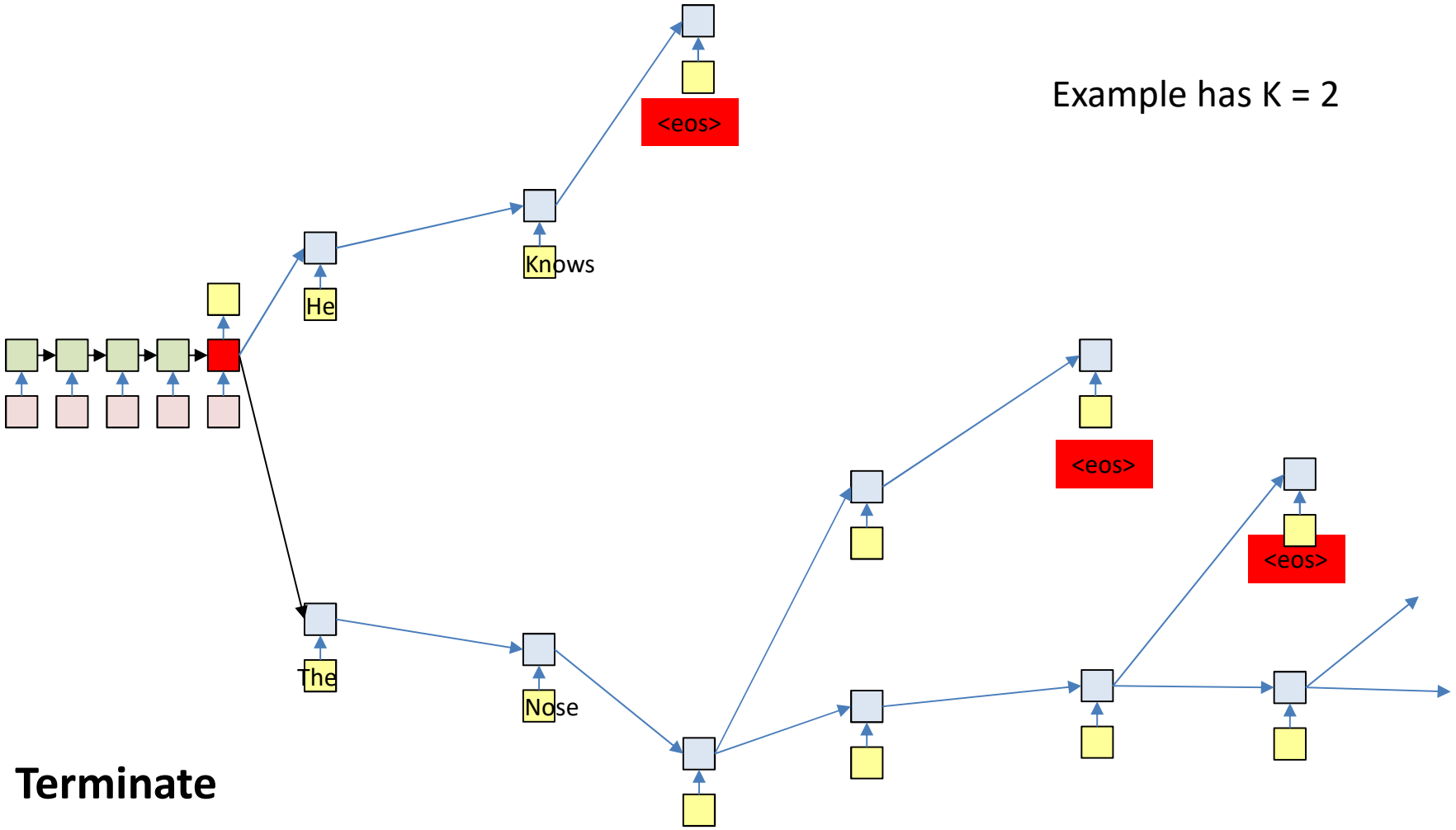
- **Solution: Prune**
  - At each time, retain only the top K scoring forks

Terminate



- **Terminate**
  - When the current most likely path overall ends in <eos>
    - Or continue producing more outputs (each of which terminates in <eos>) to get N-best outputs

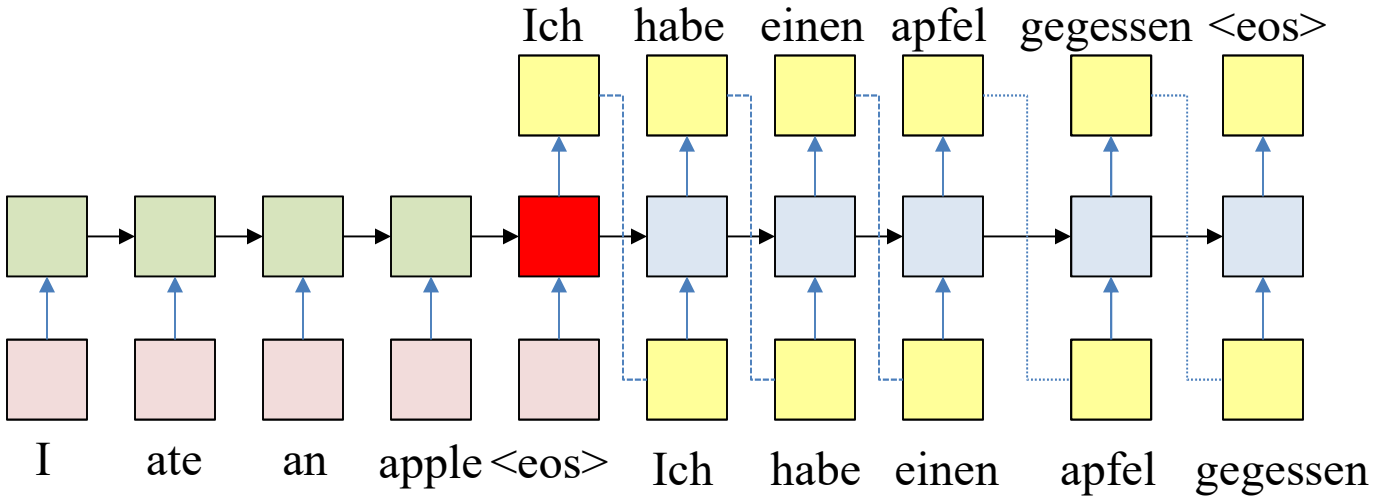
Termination: <eos>



Example has K = 2

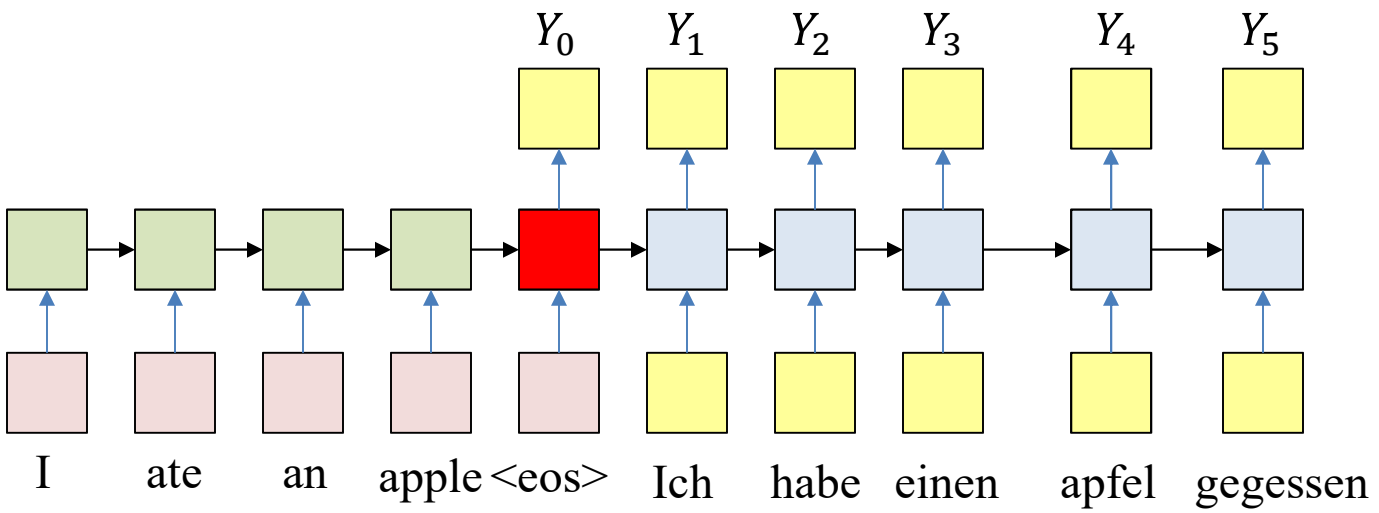
- **Terminate**
  - Paths cannot continue once the output an <eos>
    - So paths may be different lengths
      - Select the most likely sequence ending in <eos> across *all* terminating sequences

Training the system



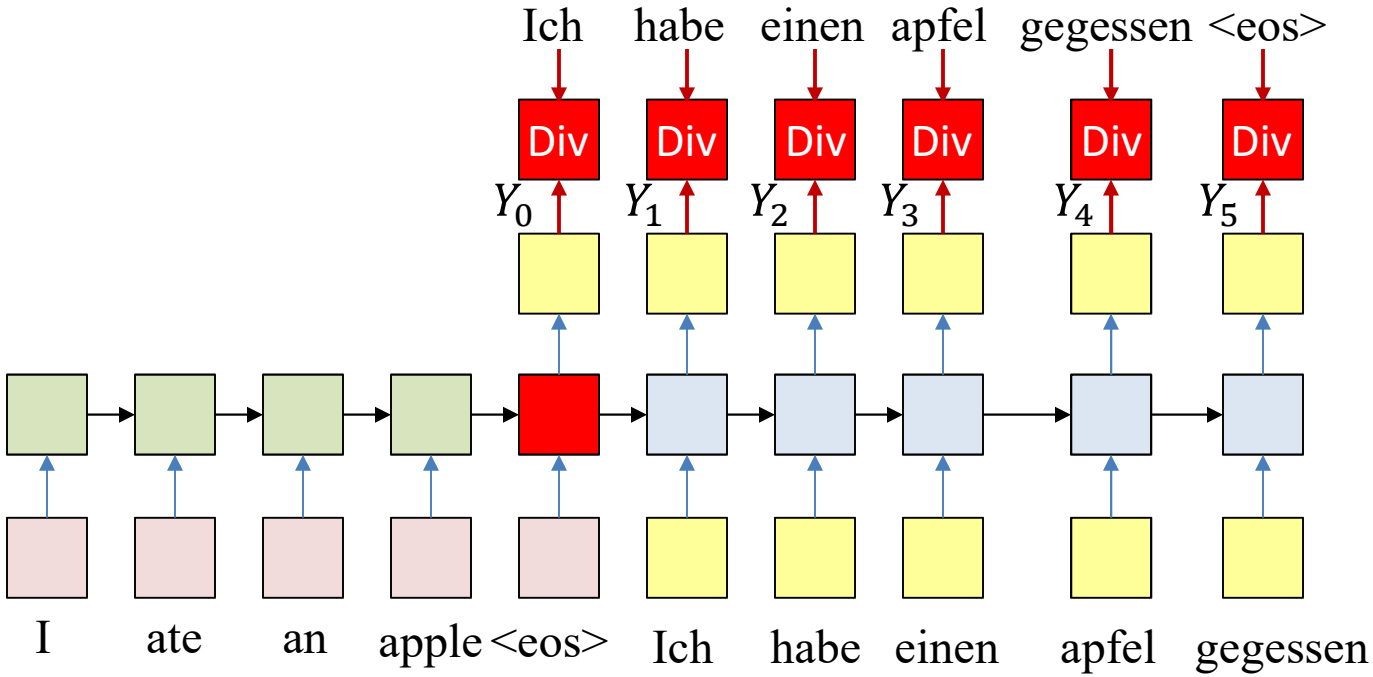
- Must learn to make predictions appropriately
  - Given “I ate an apple <eos>”, produce “Ich habe einen apfel gegessen <eos>”.

Training : Forward pass



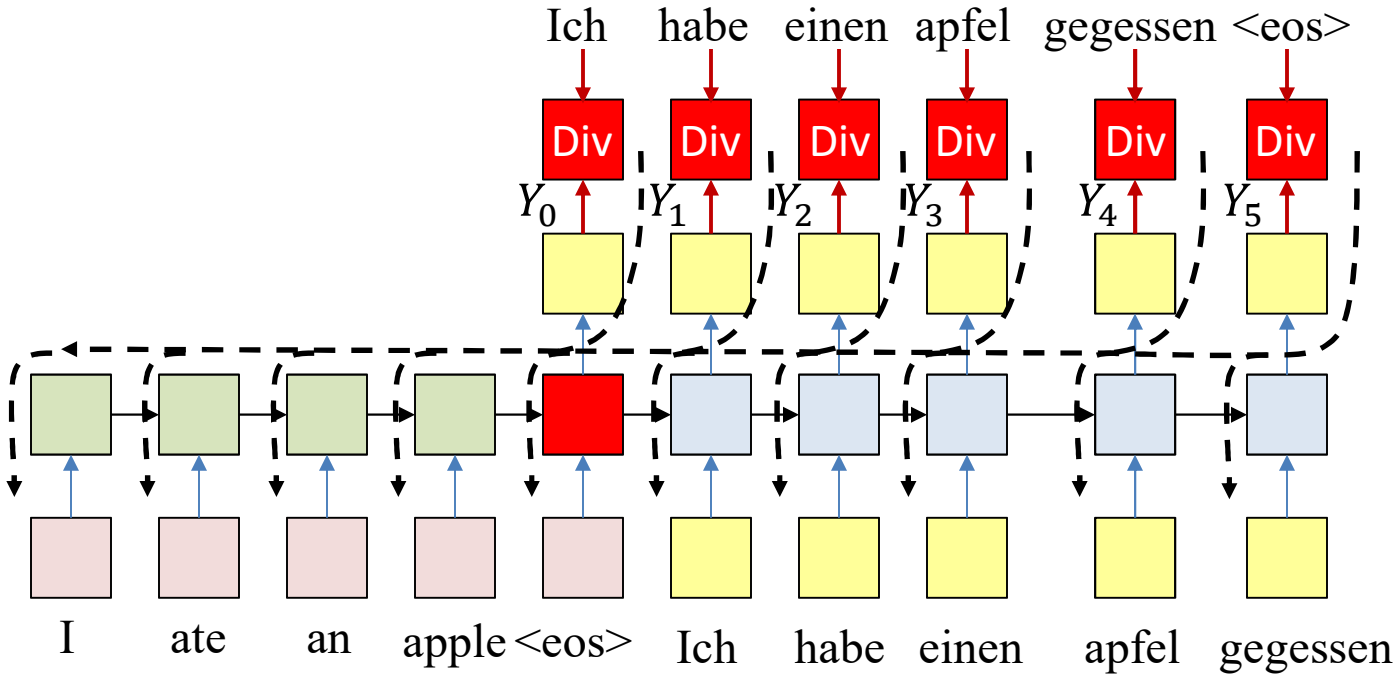
- Forward pass: Input the source and target sequences, sequentially
  - Output will be a probability distribution over target symbol set (vocabulary)

Training : Backward pass



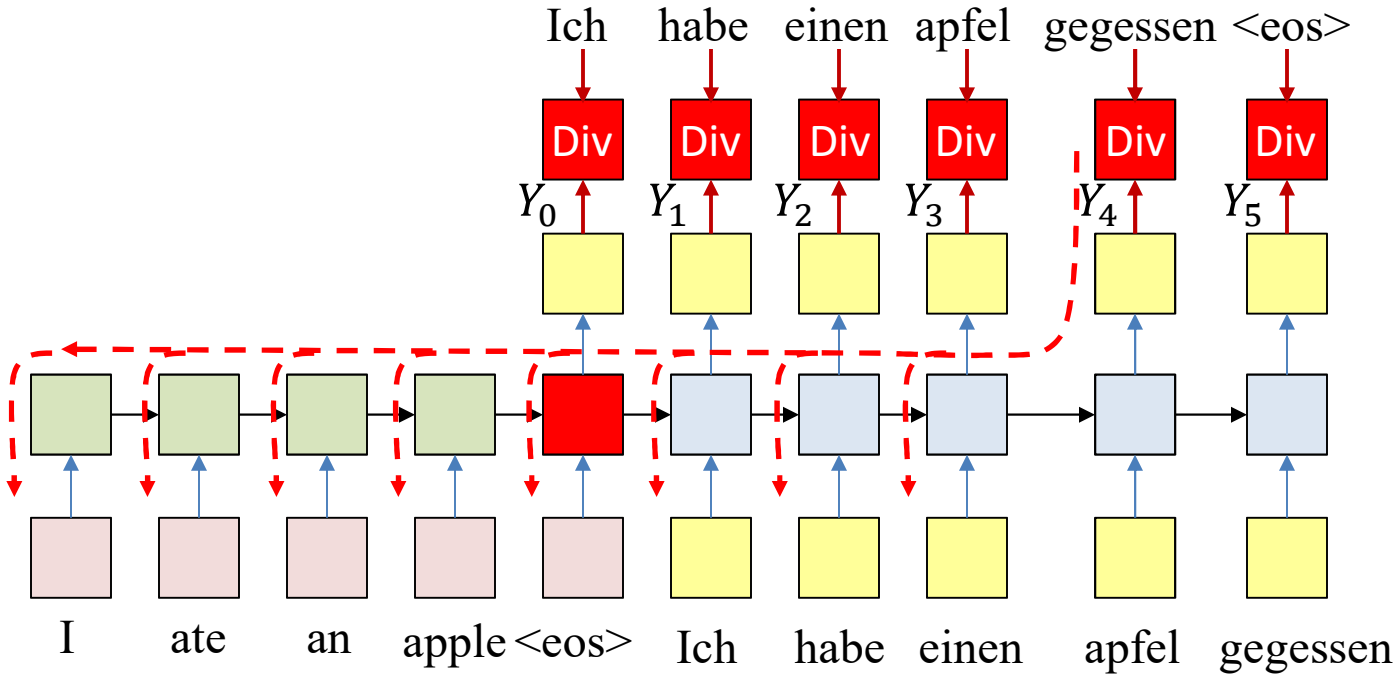
- Backward pass: Compute the divergence between the output distribution and target word sequence

Training : Backward pass



- Backward pass: Compute the divergence between the output distribution and target word sequence
- Backpropagate the derivatives of the divergence through the network to learn the net

Training : Backward pass

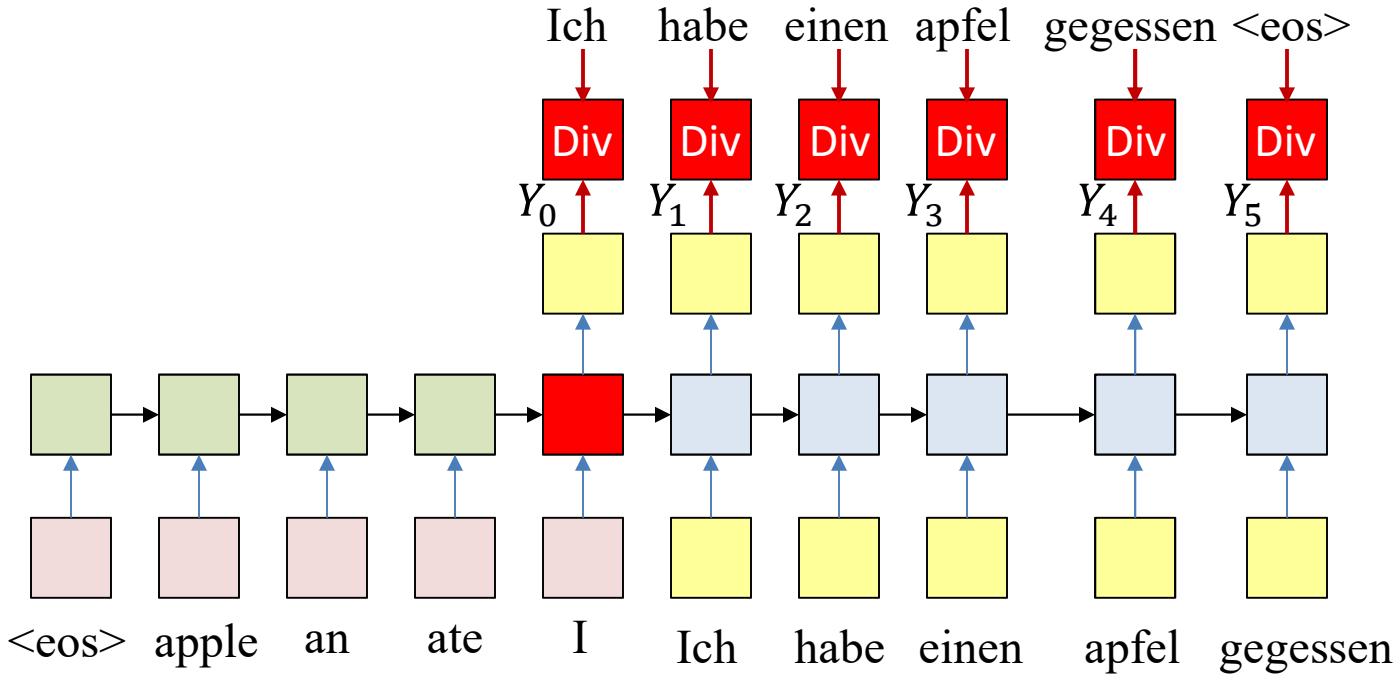


- In practice, if we apply SGD, we may randomly sample words from the output to actually use for the backprop and update
  - Typical usage: Randomly select one word from each input training instance (comprising an input-output pair)
    - For each iteration
      - Randomly select training instance: (input, output)
      - Forward pass
      - Randomly select a single output y(t) and corresponding desired output d(t) for backprop

Overall training

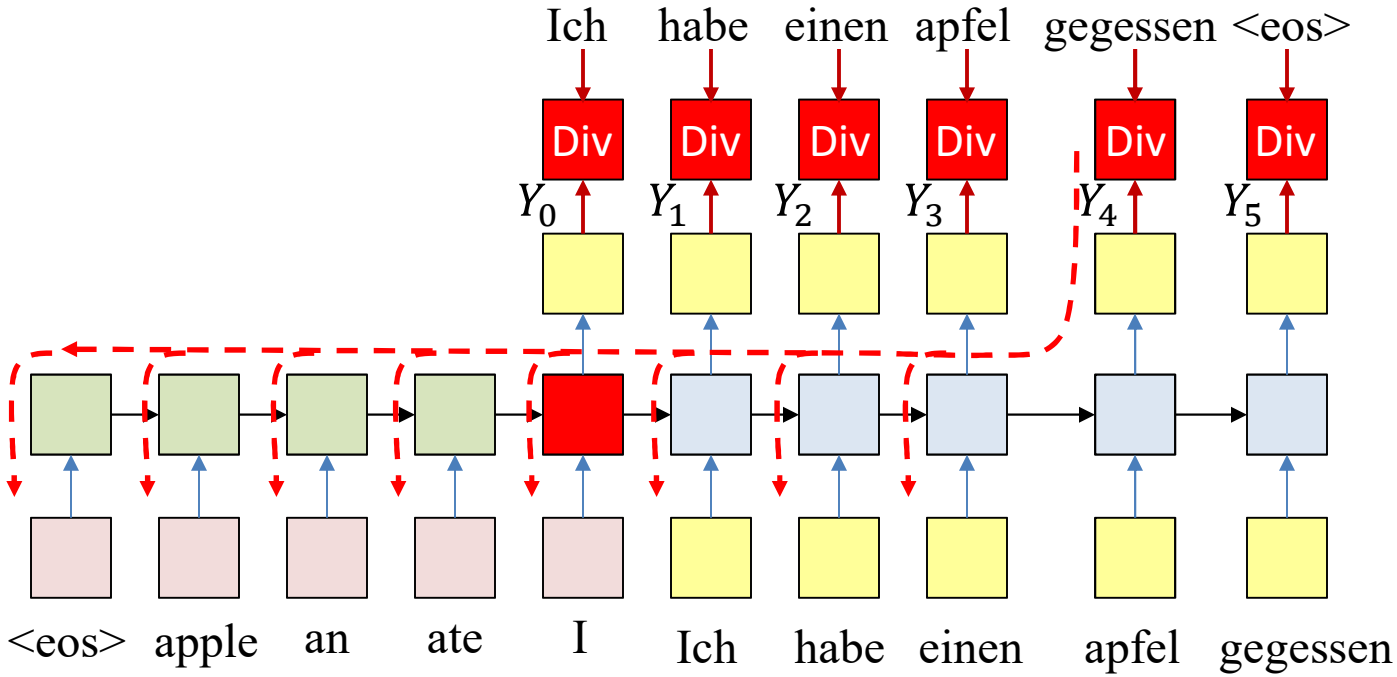
- Given several training instance $(\mathbf{X}, \mathbf{D})$
- Forward pass: Compute the output of the network for $(\mathbf{X}, \mathbf{D})$
  - Note, both $\mathbf{X}$ *and* $\mathbf{D}$ are used in the forward pass
- Backward pass: Compute the divergence between the desired target $\mathbf{D}$ and the actual output $\mathbf{Y}$
  - Propagate derivatives of divergence for updates

Trick of the trade: Reversing the input



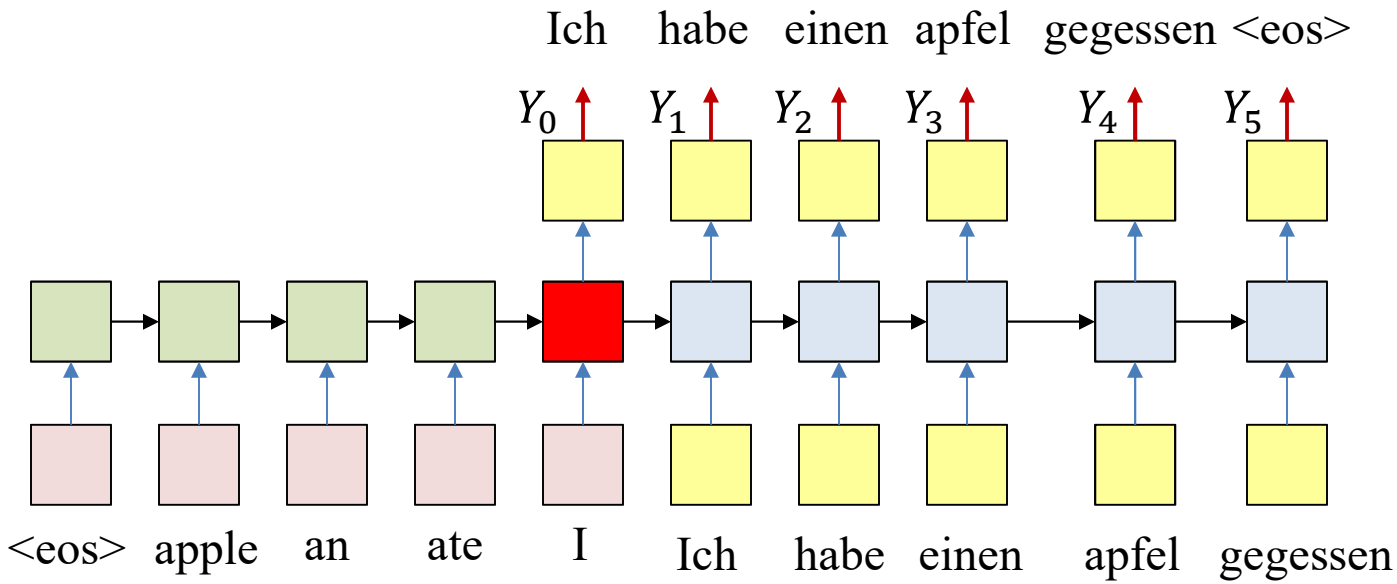
- Standard trick of the trade: The input sequence is fed *in reverse order*
  - Things work better this way

Trick of the trade: Reversing the input



- Standard trick of the trade: The input sequence is fed *in reverse order*
  - Things work better this way

Trick of the trade: Reversing the input



- Standard trick of the trade: The input sequence is fed *in reverse order*
  - Things work better this way
- *This happens both for training and during actual decode*

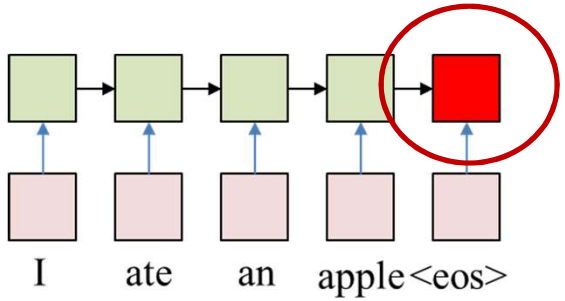
Overall training

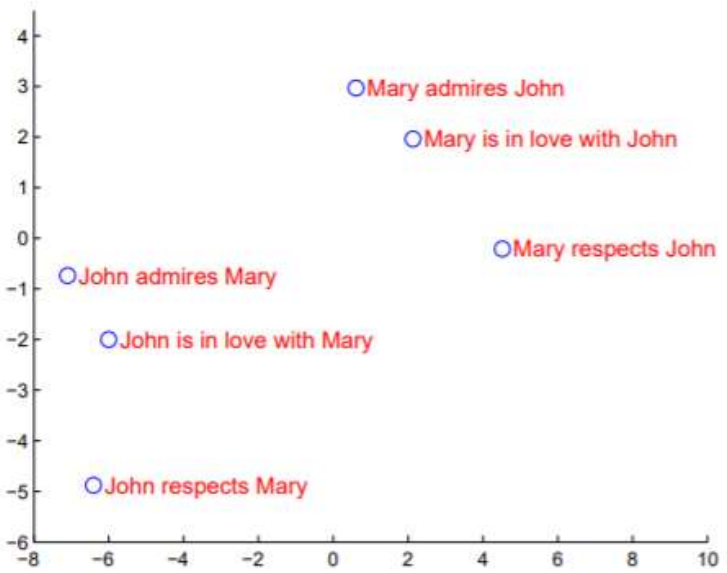
- Given several training instance $(\mathbf{X}, \mathbf{D})$
- Forward pass: Compute the output of the network for $(\mathbf{X}, \mathbf{D})$ *with input in reverse order*
  - Note, both $\mathbf{X}$ *and* $\mathbf{D}$ are used in the forward pass
- Backward pass: Compute the divergence between the desired target $\mathbf{D}$ and the actual output $\mathbf{Y}$
  - Propagate derivatives of divergence for updates

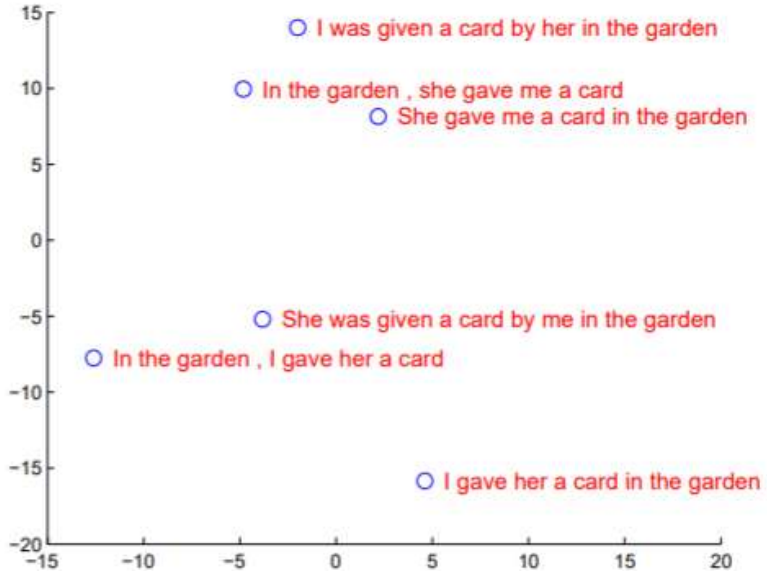
Applications

- Machine Translation
  - My name is Tom → Ich heisse Tom/Mein name ist Tom
- Automatic speech recognition
  - Speech recording → “My name is Tom”
- Dialog
  - “I have a problem” → “How may I help you”
- Image to text
  - Picture → Caption for picture

Machine Translation Example







- Hidden state clusters by meaning!
  - From “Sequence-to-sequence learning with neural networks”, Sutskever, Vinyals and Le

Machine Translation Example

Type	Sentence
Our model	Ulrich UNK , membre du conseil d' administration du constructeur automobile Audi , affirme qu' il s' agit d' une pratique courante depuis des années pour que les téléphones portables puissent être collectés avant les réunions du conseil d' administration afin qu' ils ne soient pas utilisés comme appareils d' écoute à distance .
Truth	Ulrich Hackenberg , membre du conseil d' administration du constructeur automobile Audi , déclare que la collecte des téléphones portables avant les réunions du conseil , afin qu' ils ne puissent pas être utilisés comme appareils d' écoute à distance , est une pratique courante depuis des années .
Our model	" Les téléphones cellulaires , qui sont vraiment une question , non seulement parce qu' ils pourraient potentiellement causer des interférences avec les appareils de navigation , mais nous savons , selon la FCC , qu' ils pourraient interférer avec les tours de téléphone cellulaire lorsqu' ils sont dans l' air " , dit UNK .
Truth	" Les téléphones portables sont véritablement un problème , non seulement parce qu' ils pourraient éventuellement créer des interférences avec les instruments de navigation , mais parce que nous savons , d' après la FCC , qu' ils pourraient perturber les antennes-relais de téléphonie mobile s' ils sont utilisés à bord " , a déclaré Rosenker .
Our model	Avec la crémation , il y a un " sentiment de violence contre le corps d' un être cher " , qui sera " réduit à une pile de cendres " en très peu de temps au lieu d' un processus de décomposition " qui accompagnera les étapes du deuil " .
Truth	Il y a , avec la crémation , " une violence faite au corps aimé " , qui va être " réduit à un tas de cendres " en très peu de temps , et non après un processus de décomposition , qui " accompagnerait les phases du deuil " .

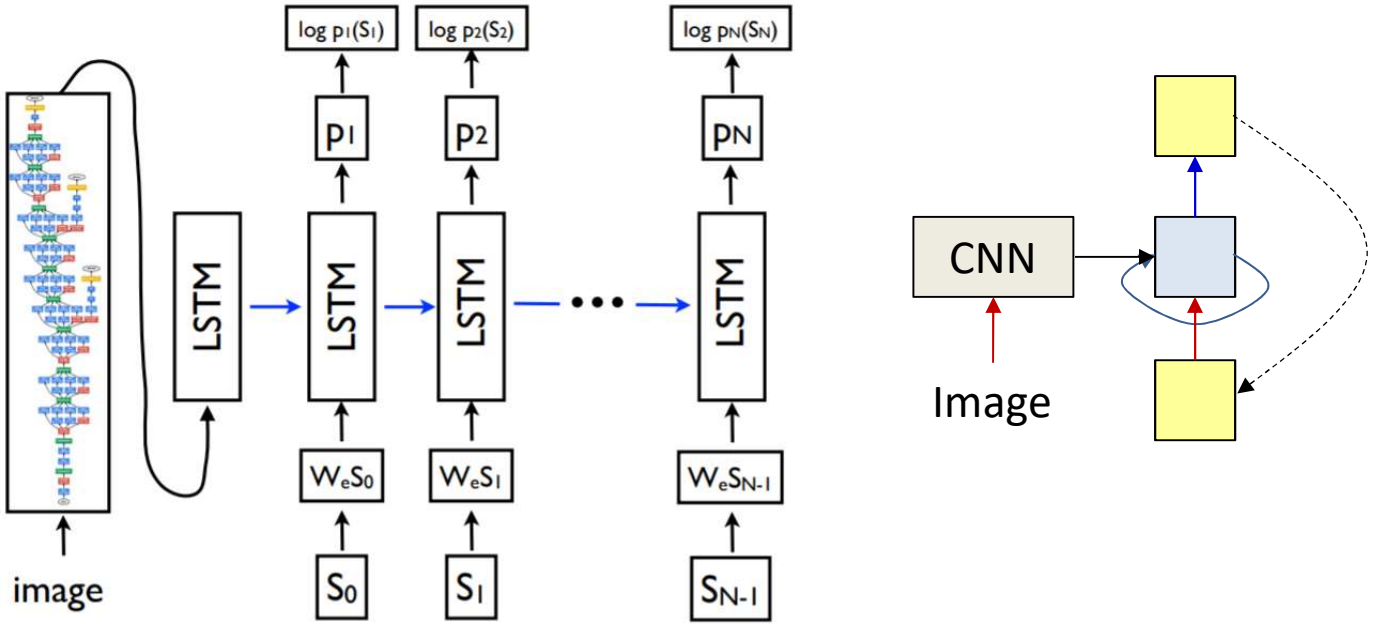
- Examples of translation
  - From "Sequence-to-sequence learning with neural networks", Sutskever, Vinyals and Le

Human Machine Conversation: Example

Machine: *what is the error that you are running please*
Human: *i am seeing an error related to vpn*
Machine: *what is the error message that you are getting when connecting to vpn using network connect ?*
Human: *connection refused or something like that*
Machine: *may i know the version of network connect you connect ?*
Human: *i am not sure i know that*
Machine: *is the network connect prompting for any user certificate*

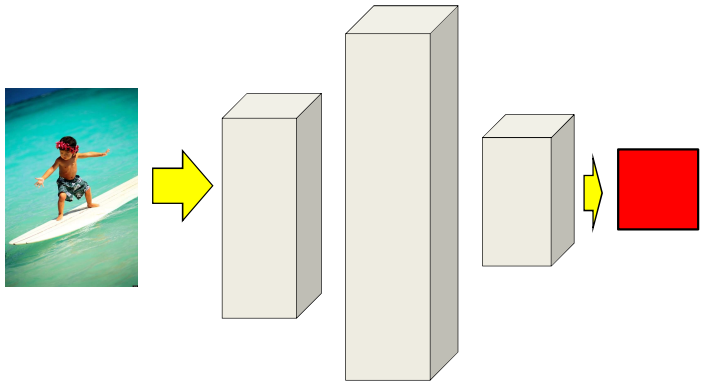
- From "A neural conversational model", Orin Vinyals and Quoc Le
- Trained on human-human converstations
- Task: Human text in, machine response out

Generating Image Captions



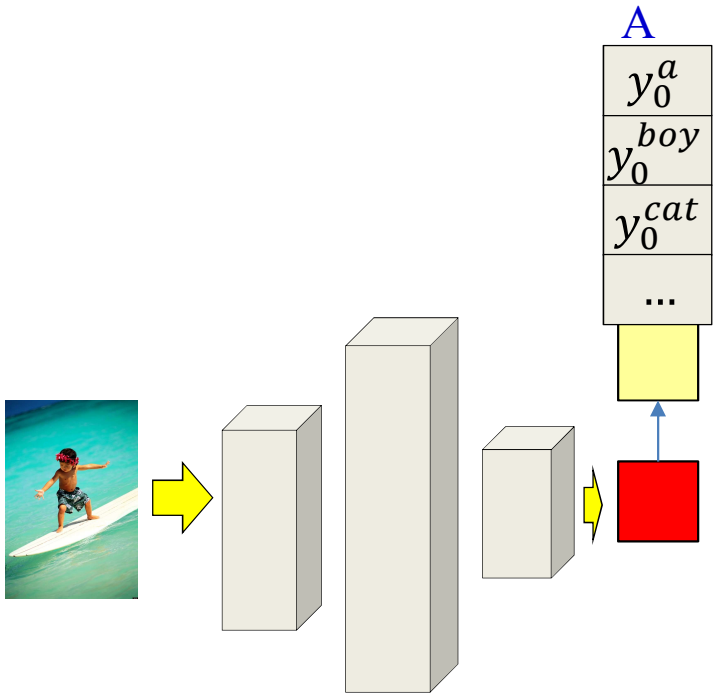
- Not really a seq-to-seq problem, more an image-to-sequence problem
- Initial state is produced by a state-of-art CNN-based image classification system
  - Subsequent model is just the decoder end of a seq-to-seq model
    - "Show and Tell: A Neural Image Caption Generator", O. Vinyals, A. Toshev, S. Bengio, D. Erhan

Generating Image Captions



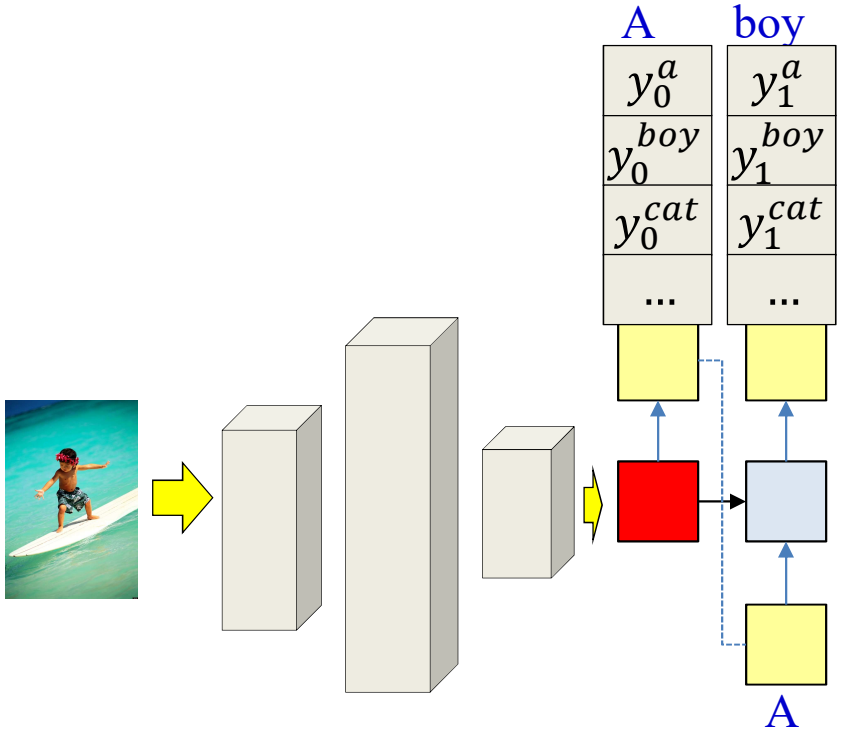
- Decoding: Given image
  - Process it with CNN to get output of classification layer

Generating Image Captions



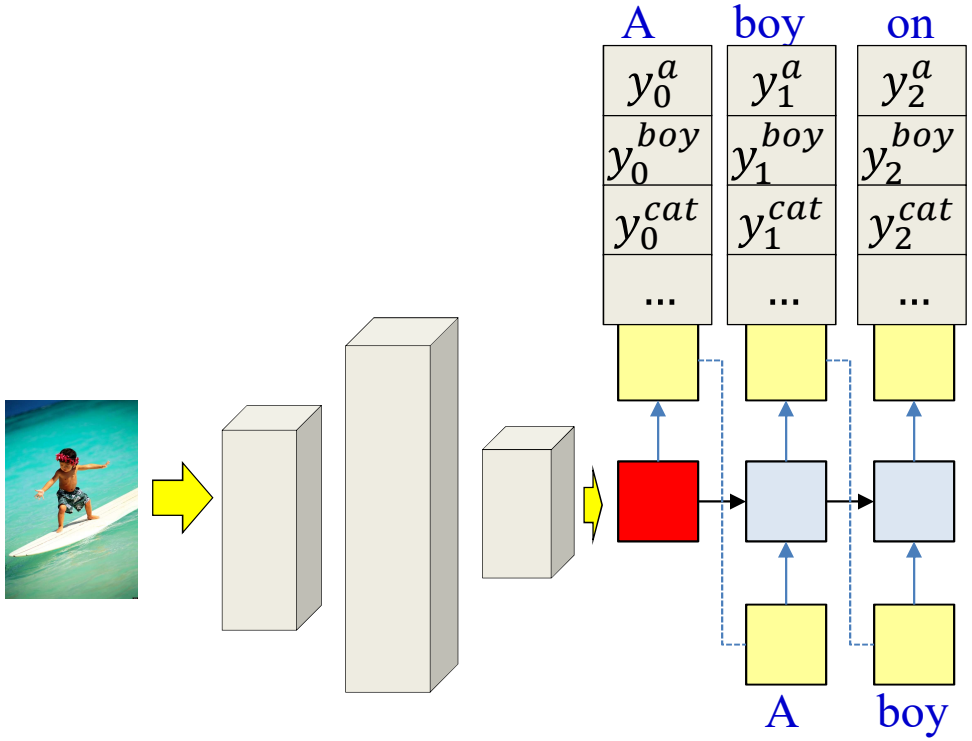
- Decoding: Given image
  - Process it with CNN to get output of classification layer
  - Sequentially generate words by drawing from the conditional output distribution $P(W_t|W_0W_1 \ldots W_{t-1}, Image)$
  - In practice, we can perform the beam search explained earlier

Generating Image Captions



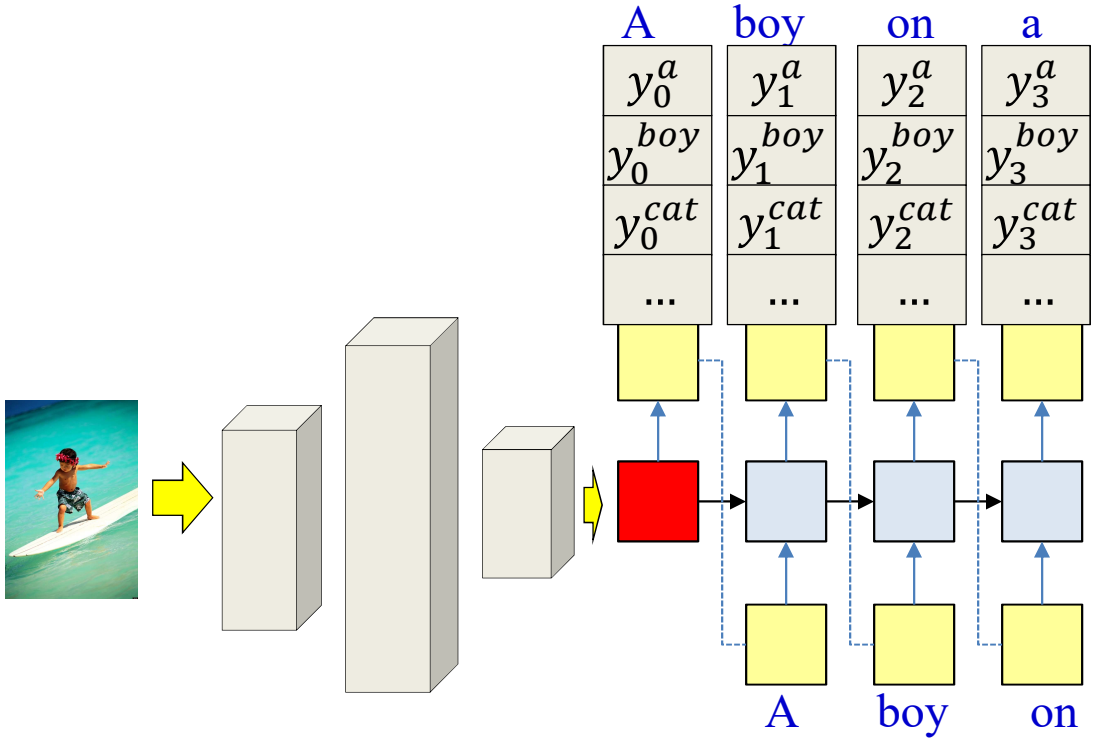
- Decoding: Given image
  - Process it with CNN to get output of classification layer
  - Sequentially generate words by drawing from the conditional output distribution $P(W_t|W_0W_1 \ldots W_{t-1}, Image)$
  - In practice, we can perform the beam search explained earlier

Generating Image Captions



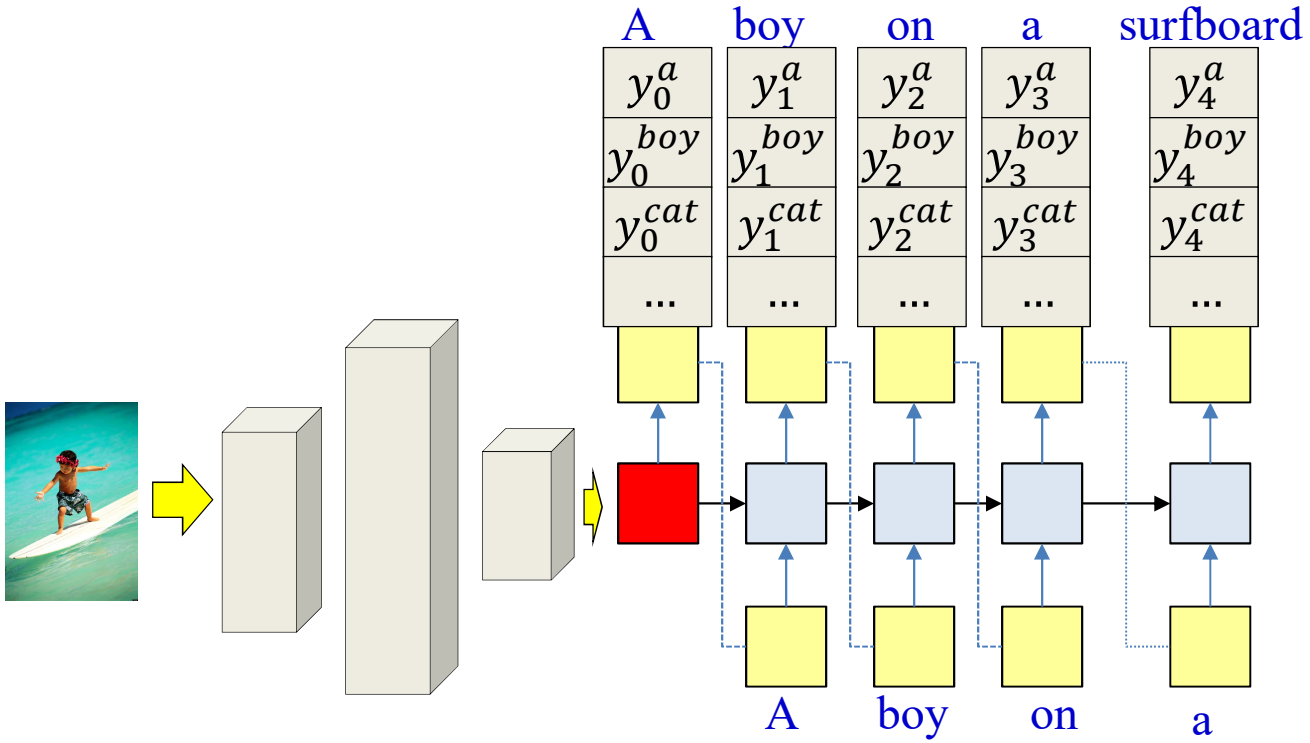
- Decoding: Given image
  - Process it with CNN to get output of classification layer
  - Sequentially generate words by drawing from the conditional output distribution $P(W_t|W_0W_1 \ldots W_{t-1}, Image)$
  - In practice, we can perform the beam search explained earlier

Generating Image Captions



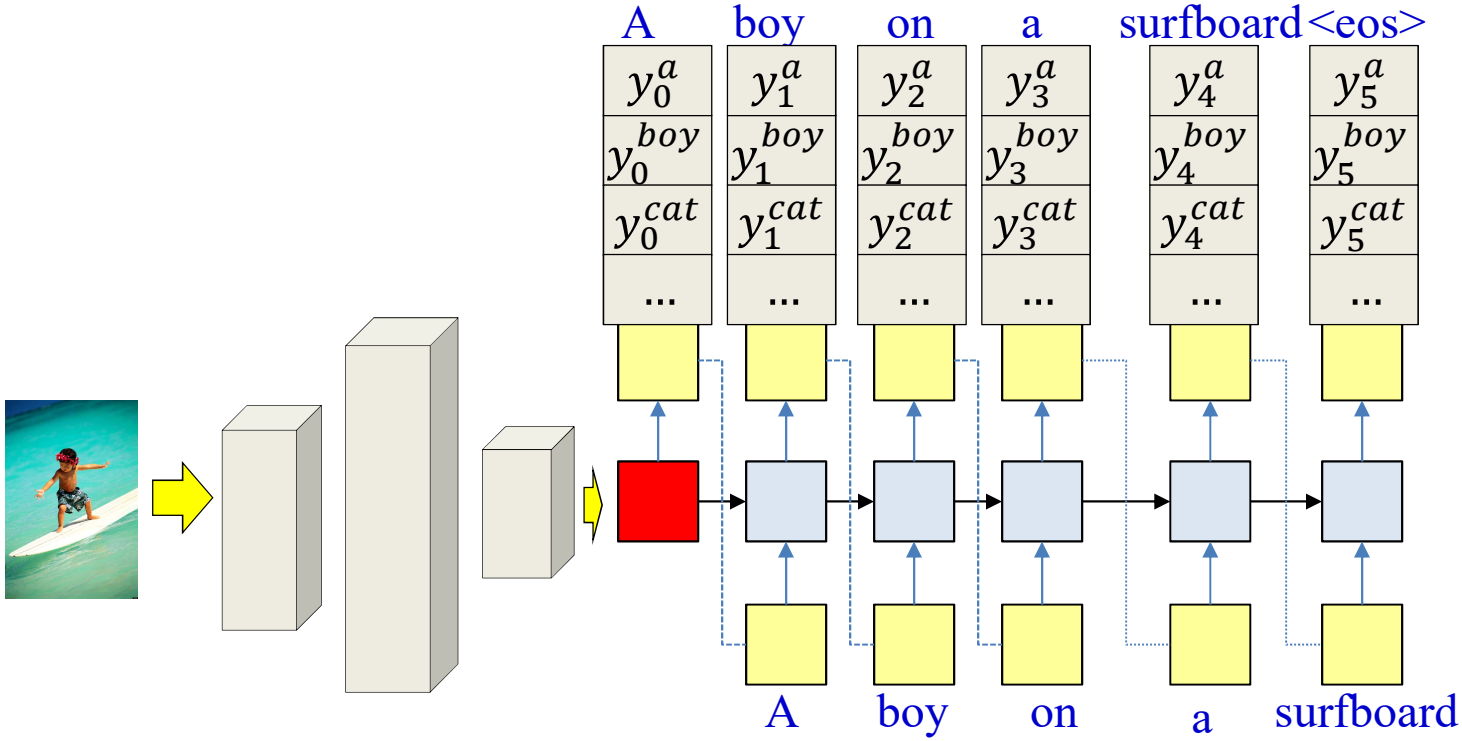
- Decoding: Given image
  - Process it with CNN to get output of classification layer
  - Sequentially generate words by drawing from the conditional output distribution $P(W_t|W_0W_1 \ldots W_{t-1}, Image)$
  - In practice, we can perform the beam search explained earlier

Generating Image Captions



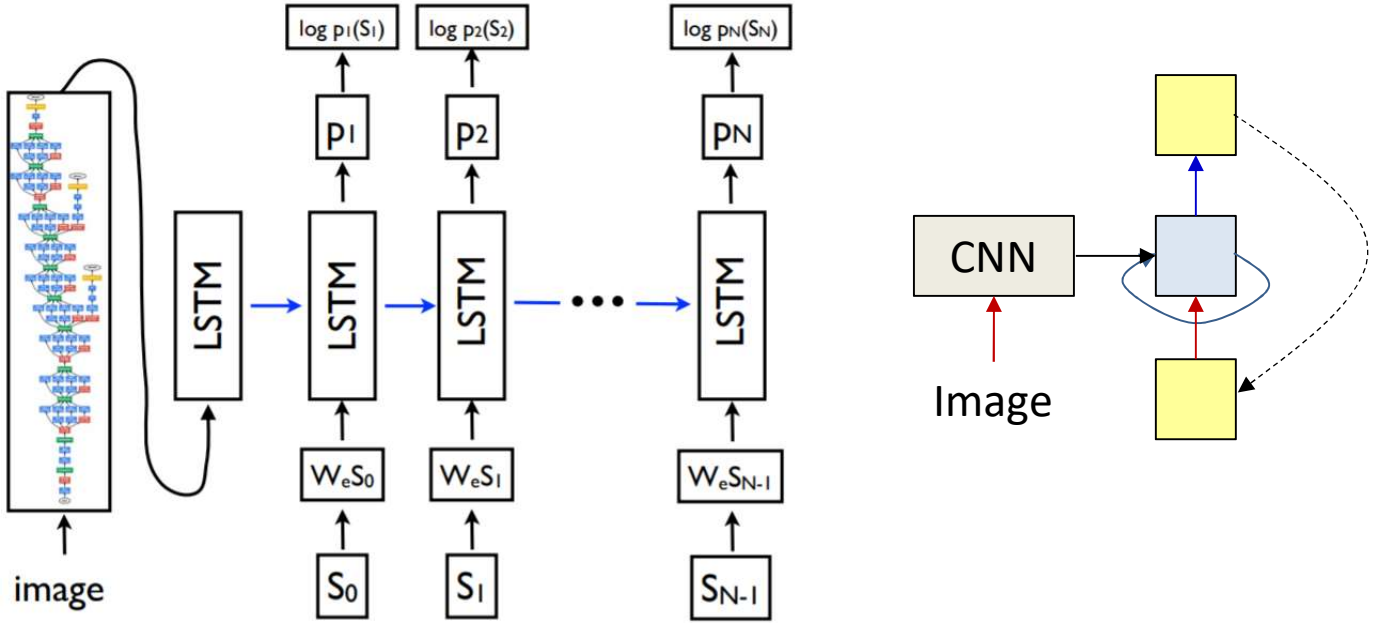
- Decoding: Given image
  - Process it with CNN to get output of classification layer
  - Sequentially generate words by drawing from the conditional output distribution $P(W_t|W_0W_1 \ldots W_{t-1}, Image)$
  - In practice, we can perform the beam search explained earlier

Generating Image Captions

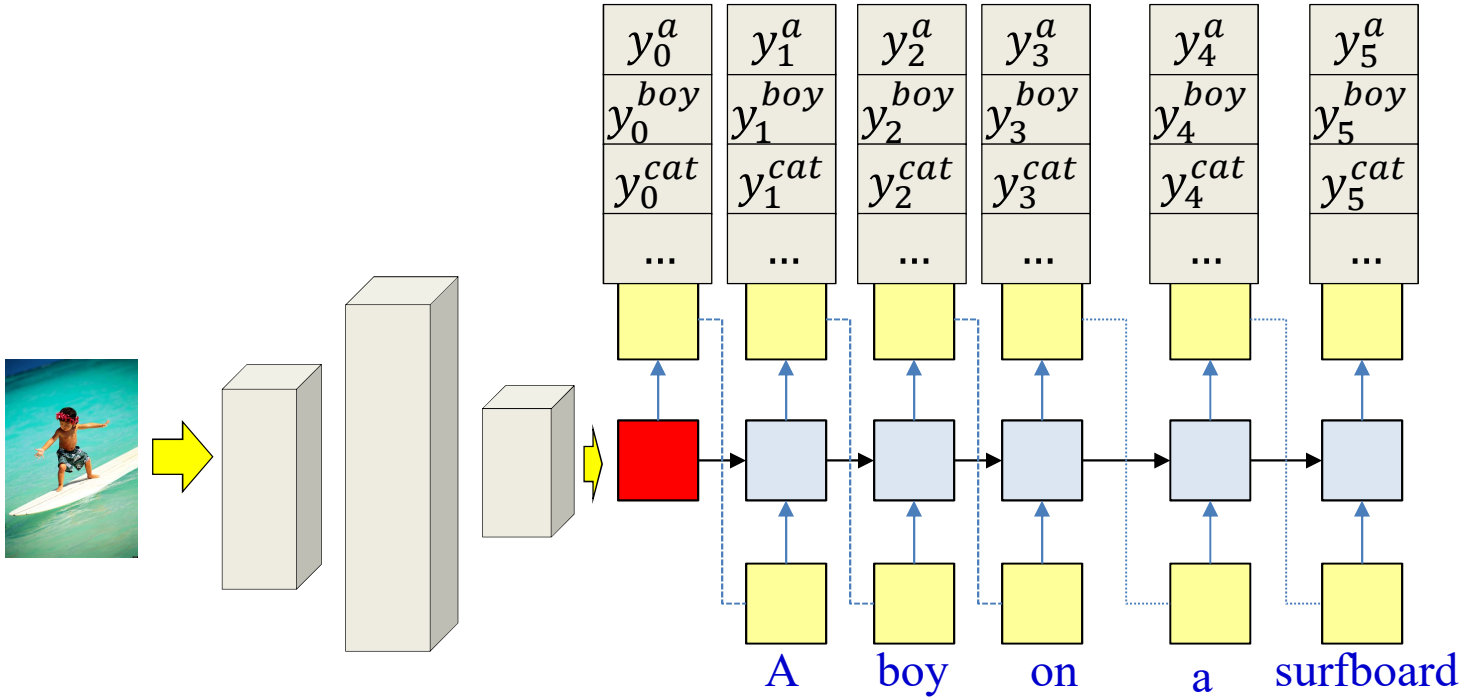


- Decoding: Given image
  - Process it with CNN to get output of classification layer
  - Sequentially generate words by drawing from the conditional output distribution $P(W_t|W_0W_1 \ldots W_{t-1}, Image)$
  - In practice, we can perform the beam search explained earlier

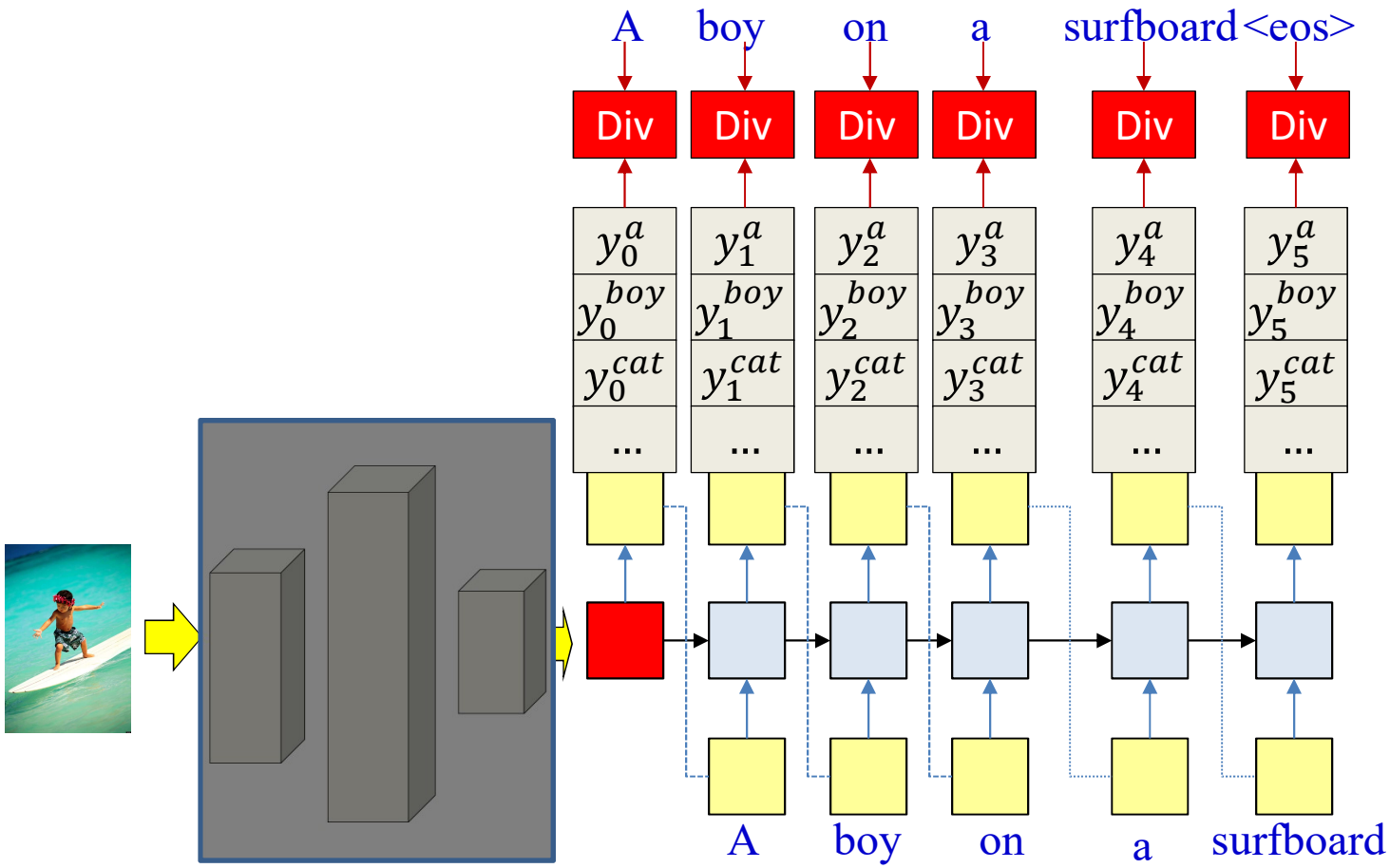
Training



- **Training**: Given several (Image, Caption) pairs
  - The image network is pretrained on a large corpus, e.g. image net



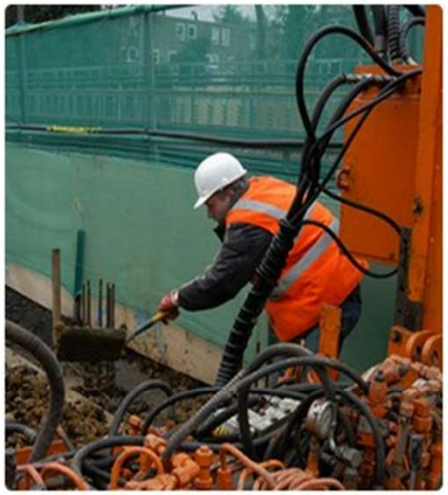
- **Training**: Given several (Image, Caption) pairs
  - The image network is pretrained on a large corpus, e.g. image net
- **Forward pass:** Produce output distributions given the image and caption



- **Training**: Given several (Image, Caption) pairs
  - The image network is pretrained on a large corpus, e.g. image net
- **Forward pass:** Produce output distributions given the image and caption
- **Backward pass:** Compute the divergence w.r.t. training caption, and backpropagate derivatives
  - All components of the network, including final classification layer of the image classification net are updated
  - The CNN portions of the image classifier are not modified (transfer learning)

Examples from Vinyals et. Al.

"man in black shirt is playing guitar."



"construction worker in orange safety vest is working on road."

"two young girls are playing with lego toy."

"boy is doing backflip on wakeboard."

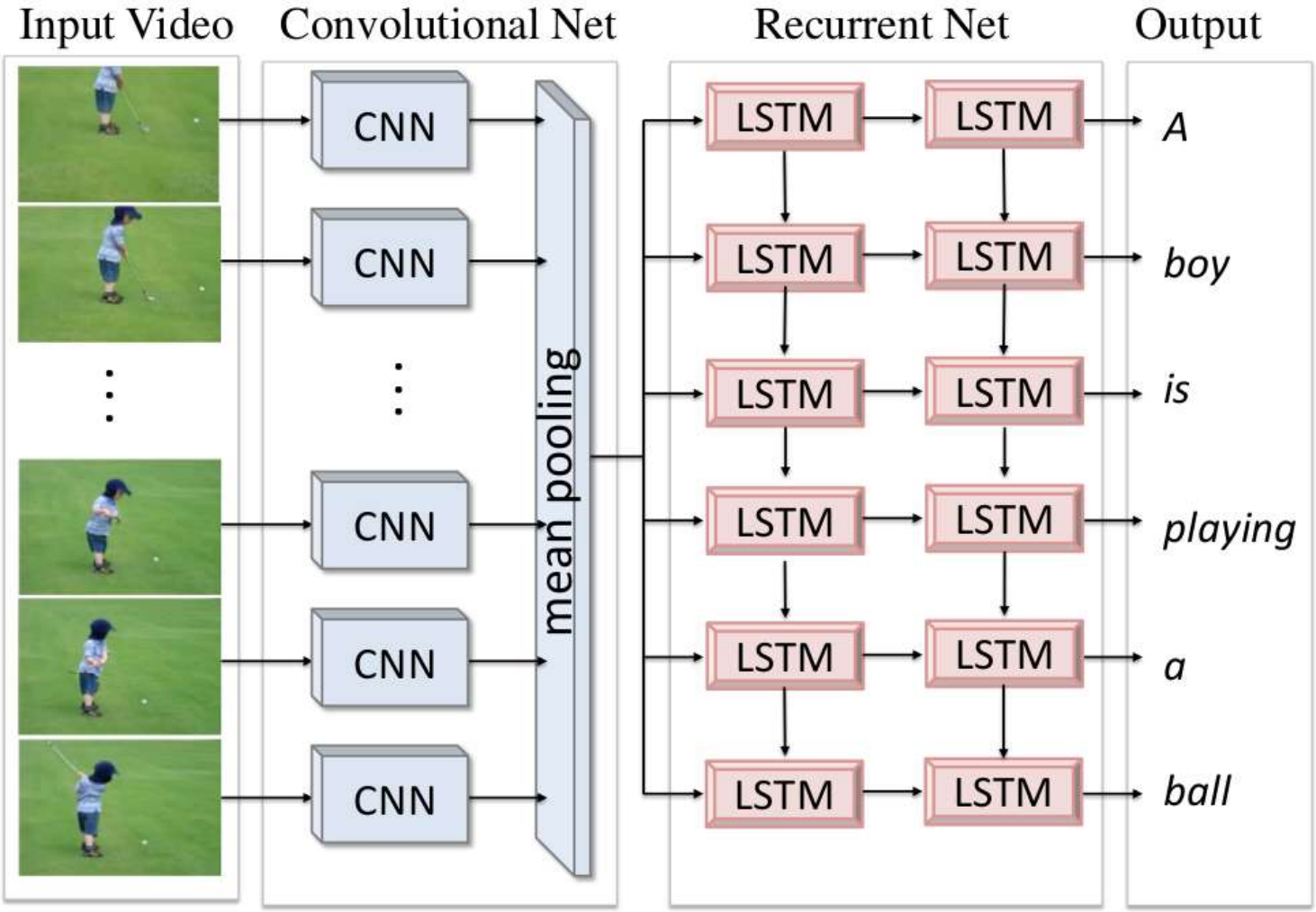
"a young boy is holding a baseball bat."

"a cat is sitting on a couch with a remote control."

"a woman holding a teddy bear in front of a mirror."

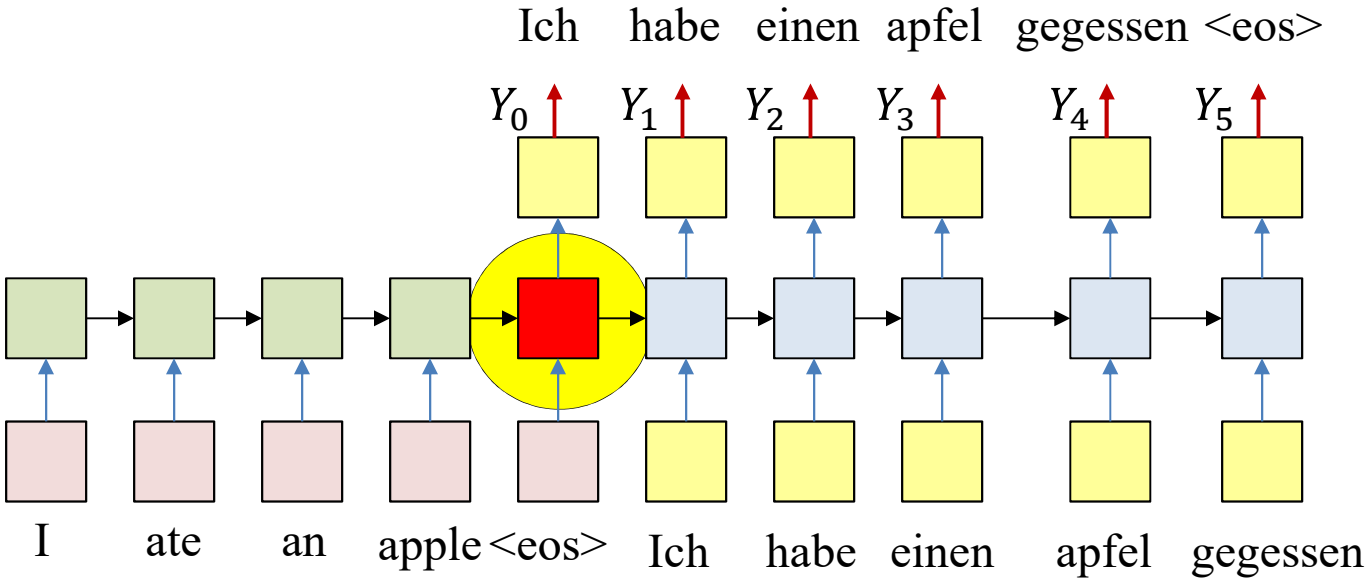
"a horse is standing in the middle of a road."

Translating Videos to Natural Language Using Deep Recurrent Neural Networks



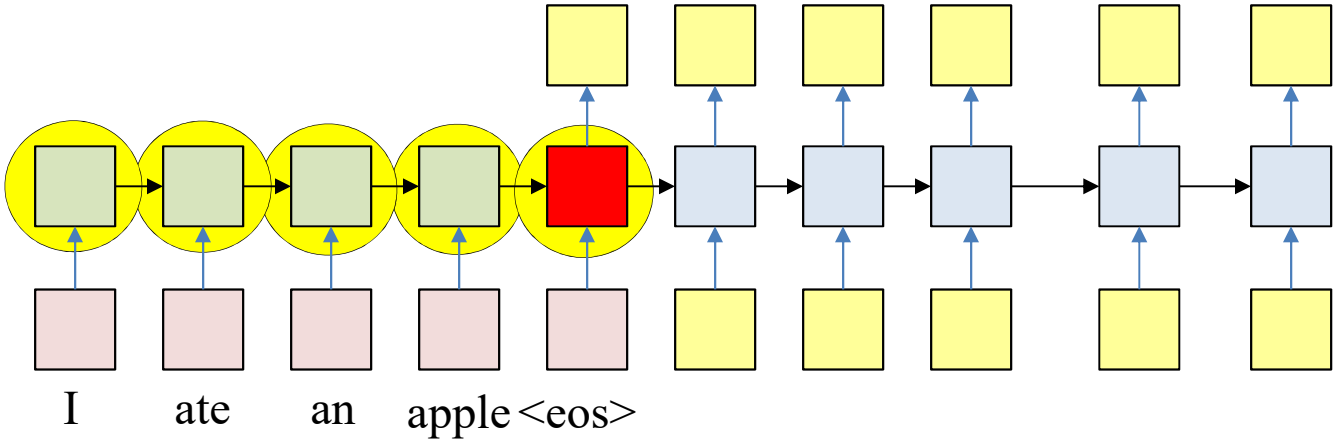
Translating Videos to Natural Language Using Deep Recurrent Neural Networks
Subhashini Venugopalan, Huijun Xu, Jeff Donahue, Marcus Rohrbach, Raymond Mooney, Kate Saenko
North American Chapter of the Association for Computational Linguistics, Denver, Colorado, June 2015.

A problem with this framework



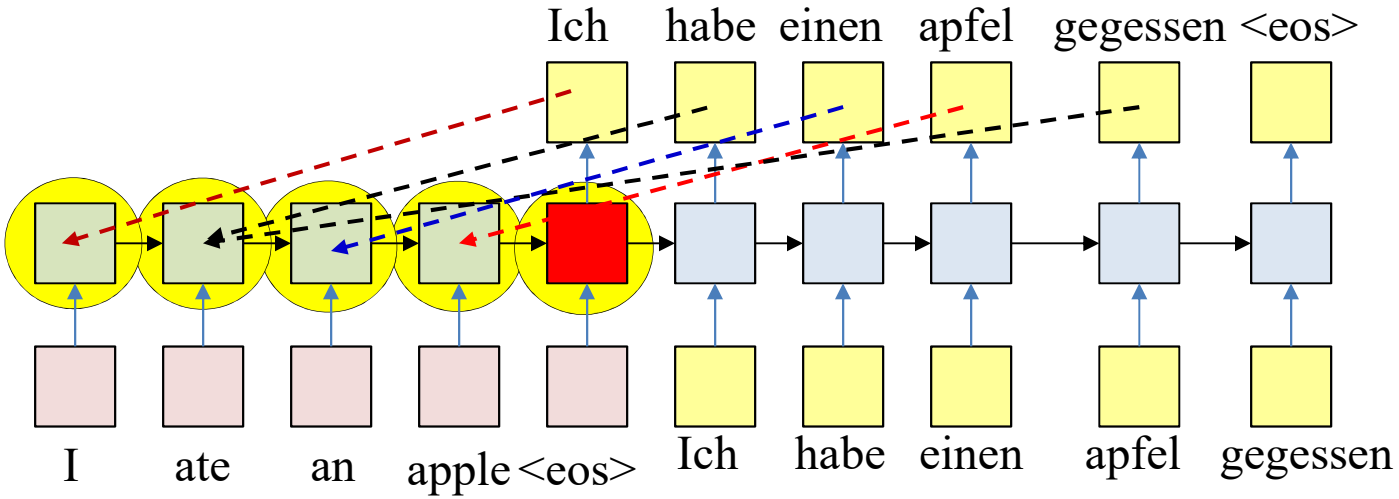
- *All* the information about the input sequence is embedded into a *single* vector
  - The "hidden" node layer at the end of the input sequence
  - This one node is "overloaded" with information
    - Particularly if the input is long

A problem with this framework



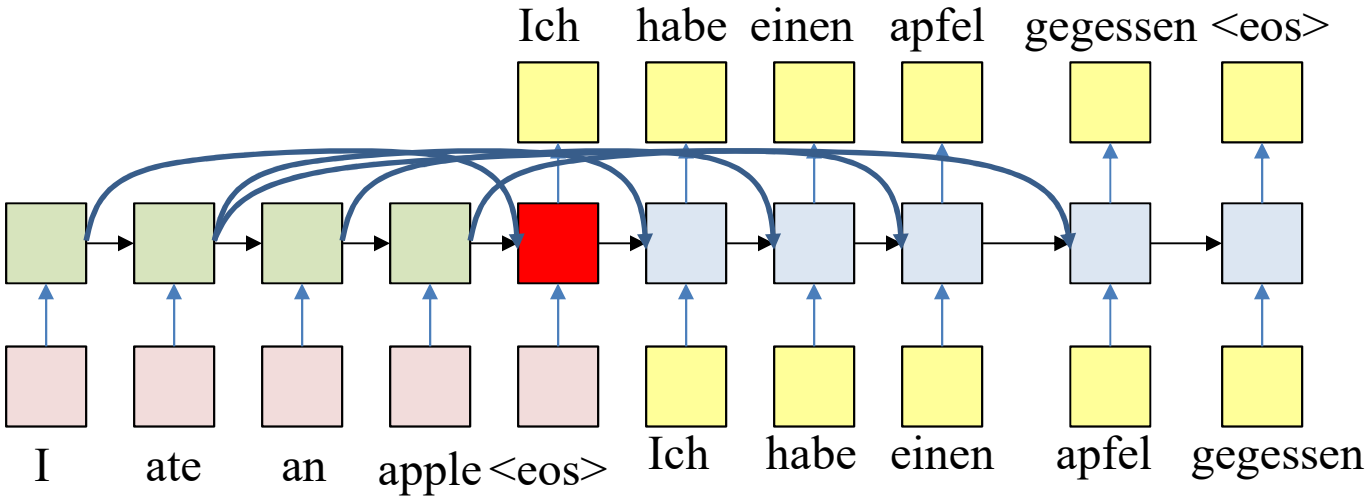
- In reality: *All* hidden values carry information
  - Some of which may be diluted downstream

A problem with this framework



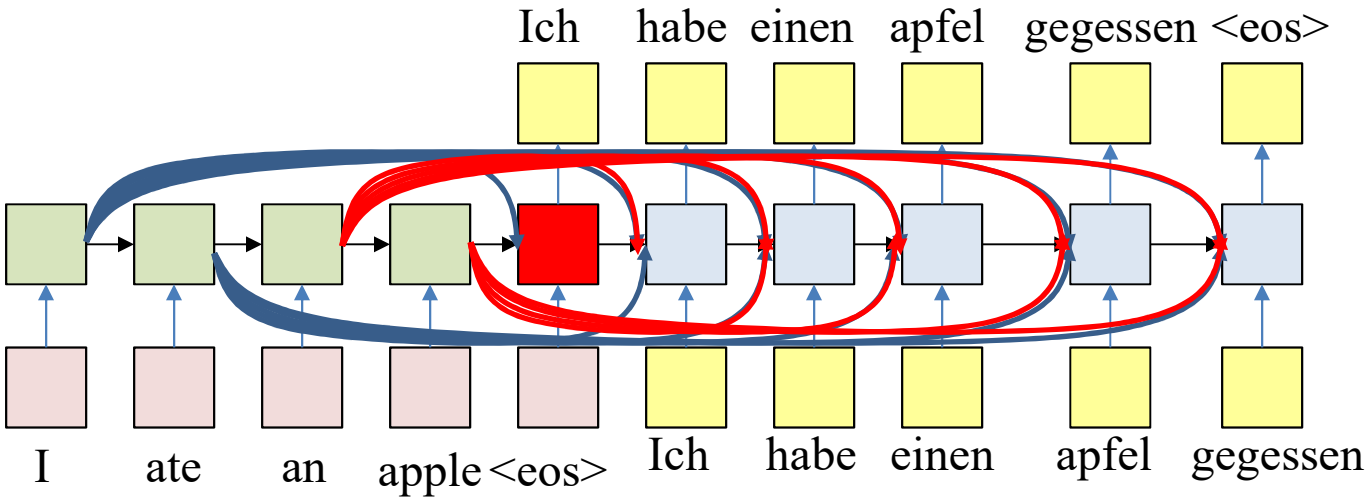
- In reality: *All* hidden values carry information
  - Some of which may be diluted downstream
- Different outputs are related to different inputs
  - Recall input and output may not be in sequence

A problem with this framework



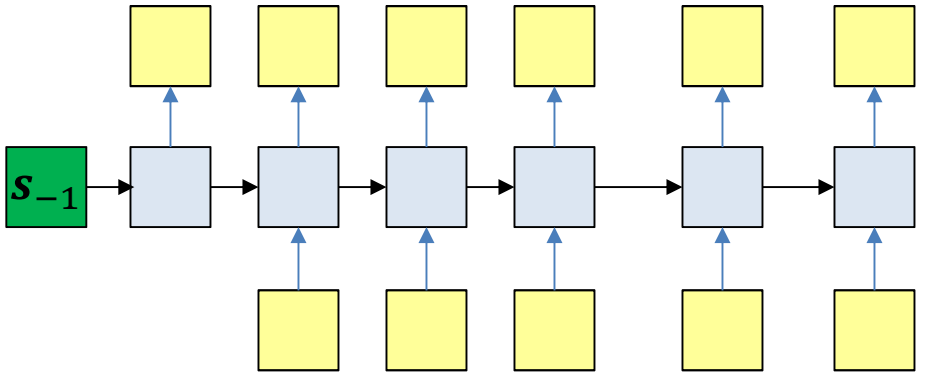
- In reality: *All* hidden values carry information
  - Some of which may be diluted downstream
- Different outputs are related to different inputs
  - Recall input and output may not be in sequence
  - Have no way of knowing a priori which input must connect to what output

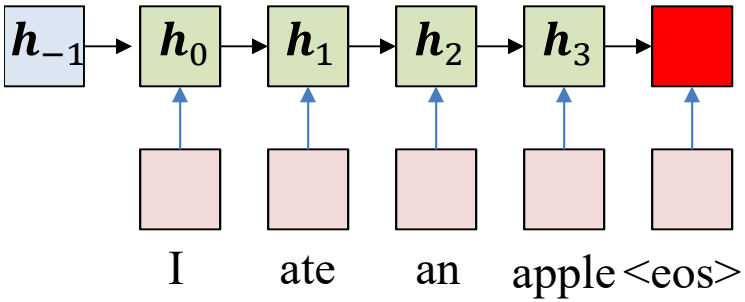
A problem with this framework



- In reality: *All* hidden values carry information
  - Some of which may be diluted downstream
- Different outputs are related to different inputs
  - Recall input and output may not be in sequence
  - Have no way of knowing a priori which input must connect to what output
- Connecting everything to everything is infeasible
  - Variable sized inputs and outputs
  - Overparametrized
  - Connection pattern ignores the actual asynchronous dependence of output on input

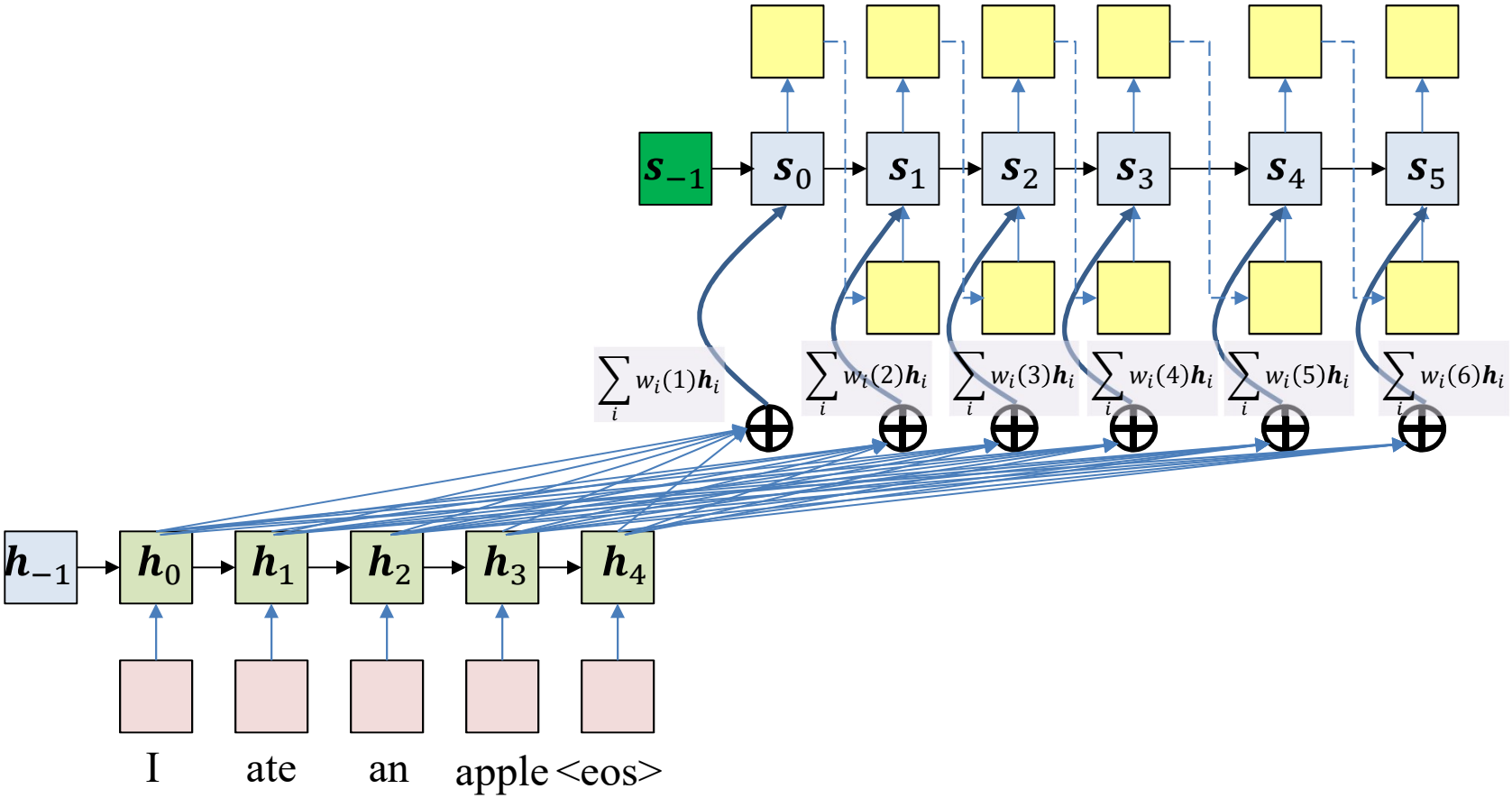
Solution: Attention models





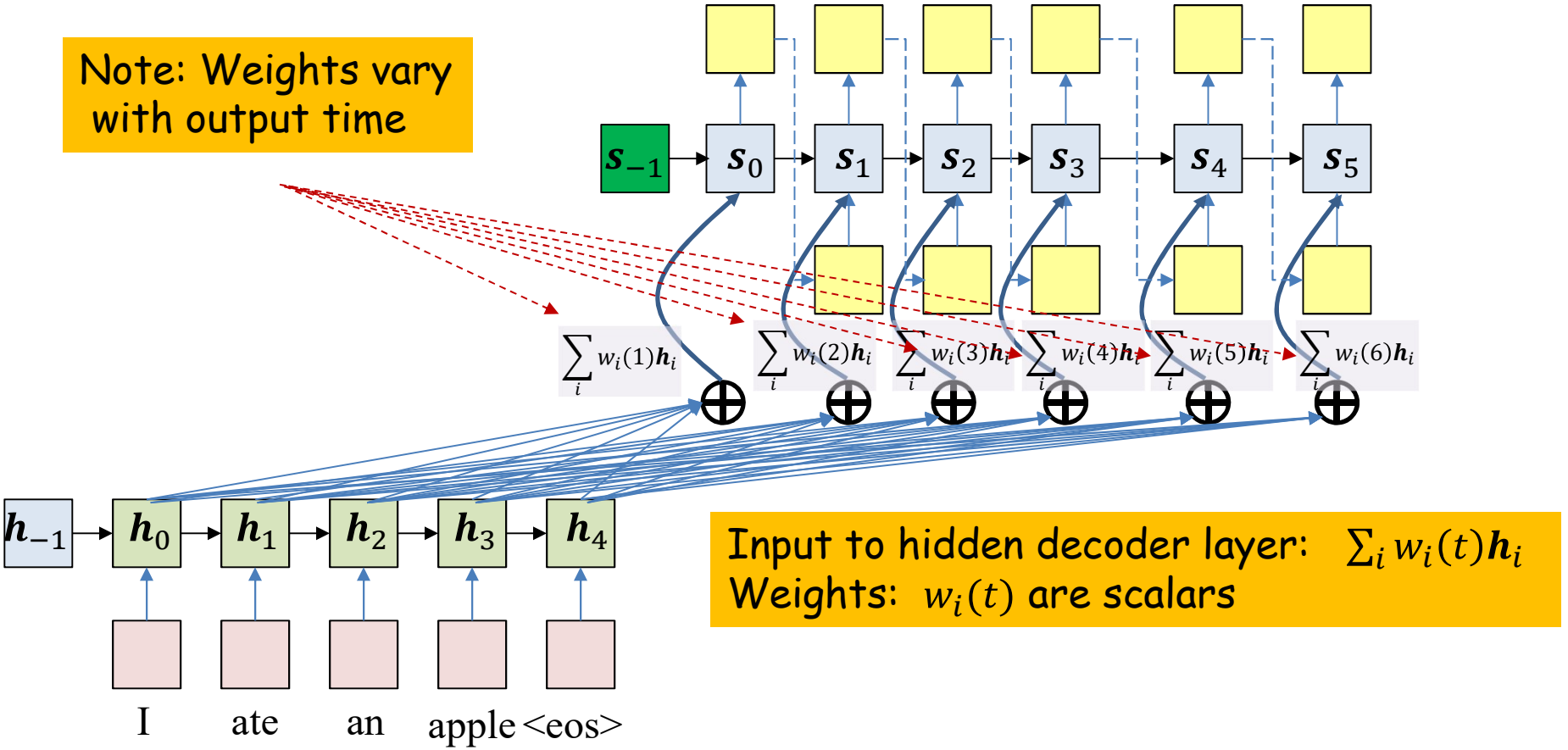
- Separating the encoder and decoder in illustration

Solution: Attention models



- Compute a weighted combination of all the hidden outputs into a single vector
  - Weights vary by output time

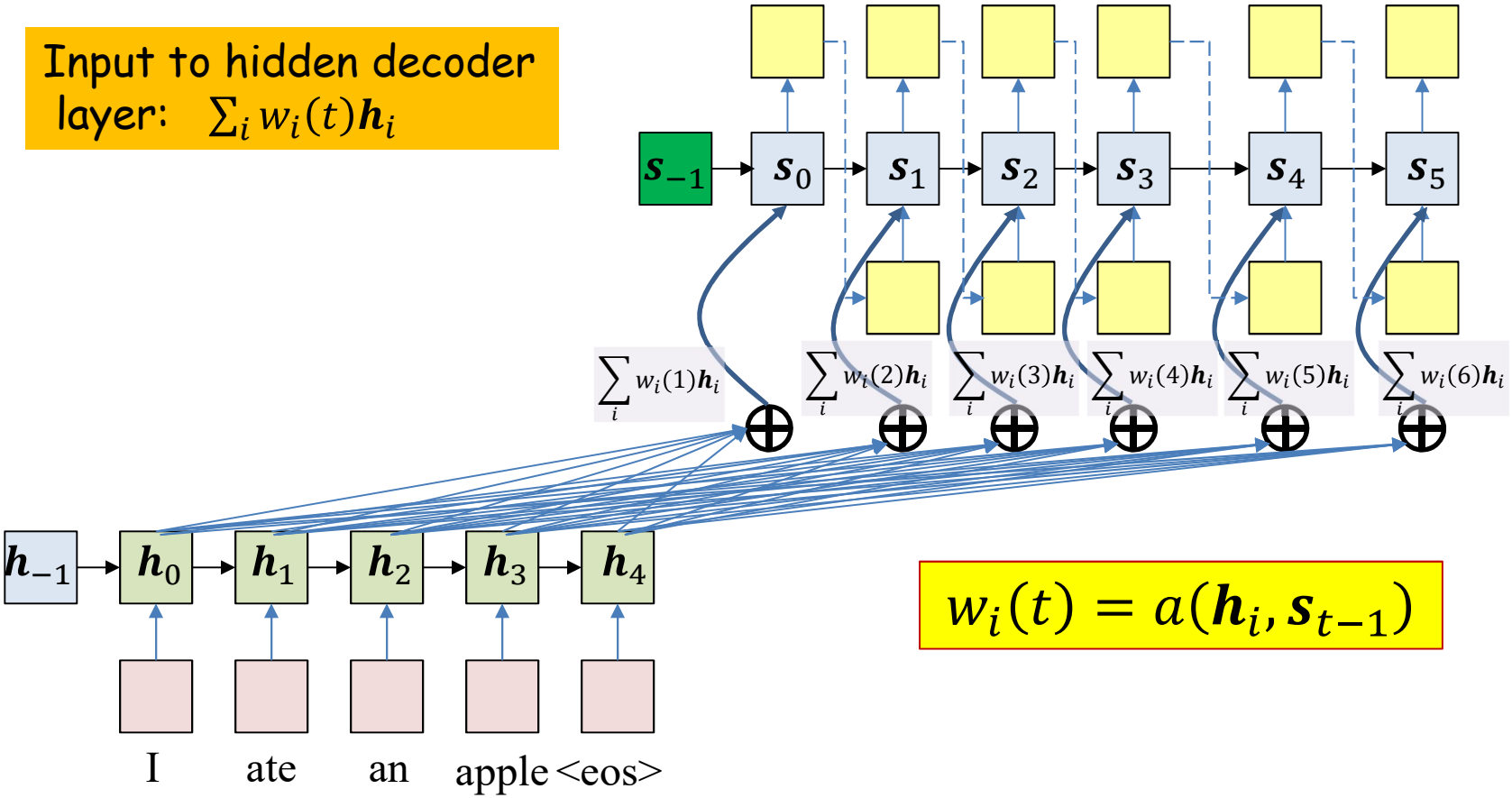
Solution: Attention models



- Compute a weighted combination of all the hidden outputs into a single vector
  - Weights vary by output time

Solution: Attention models

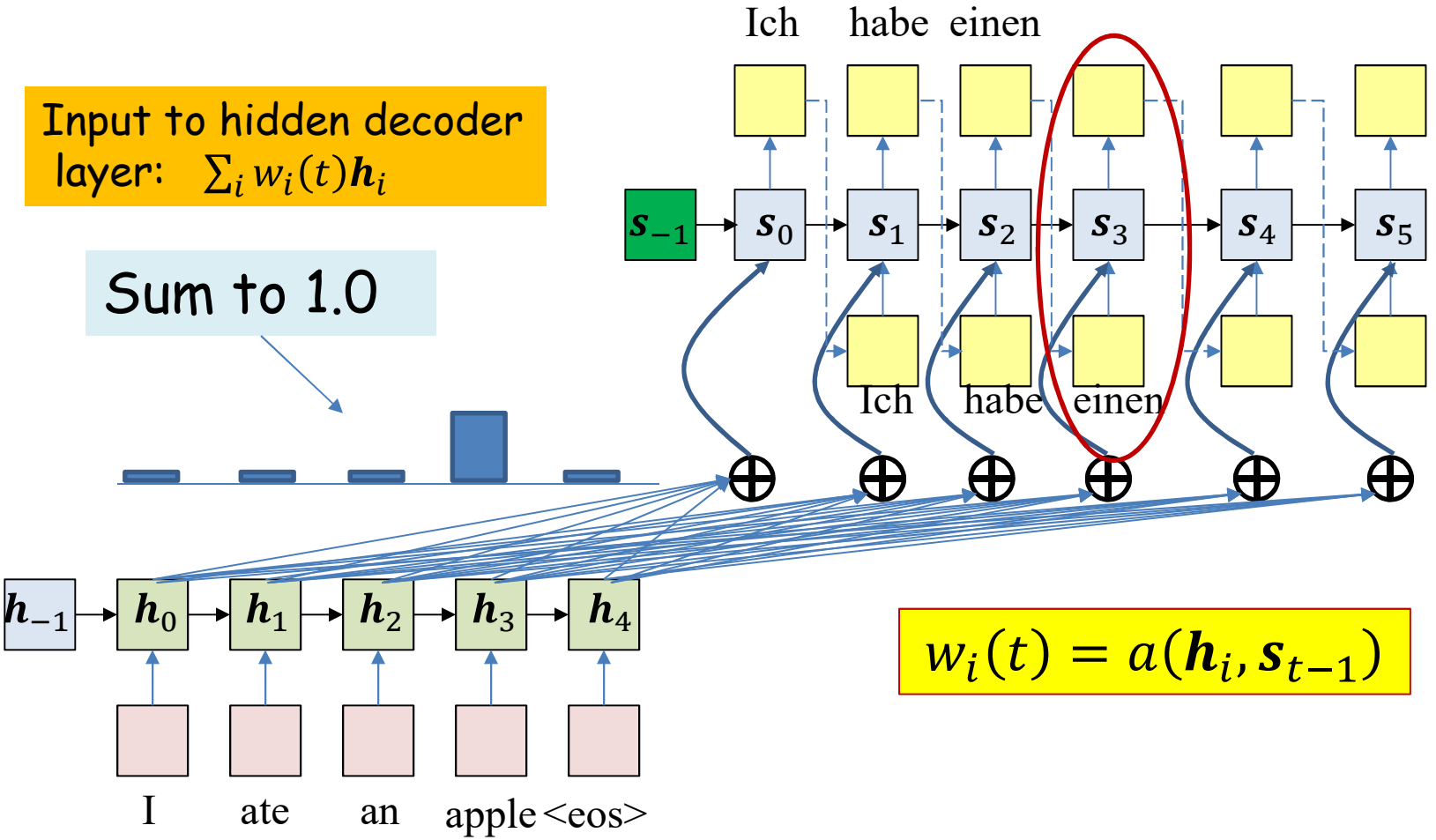
Input to hidden decoder layer: $\sum_i w_i(t)\boldsymbol{h}_i$



$$w_i(t) = a(\boldsymbol{h}_i, \boldsymbol{s}_{t-1})$$

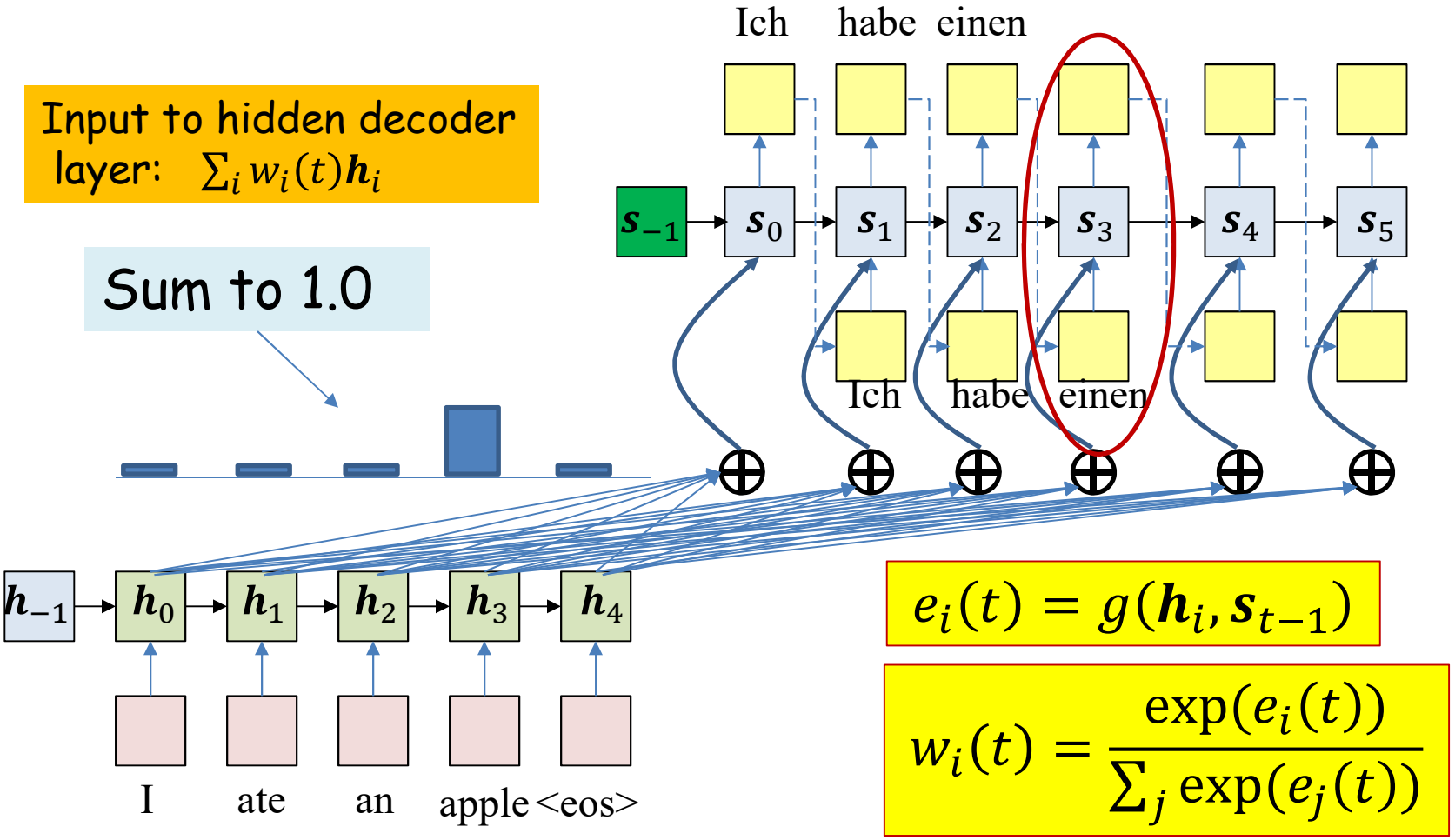
- Require a time-varying weight that specifies relationship of output time to input time
  - Weights are *functions* of current output state

Attention models



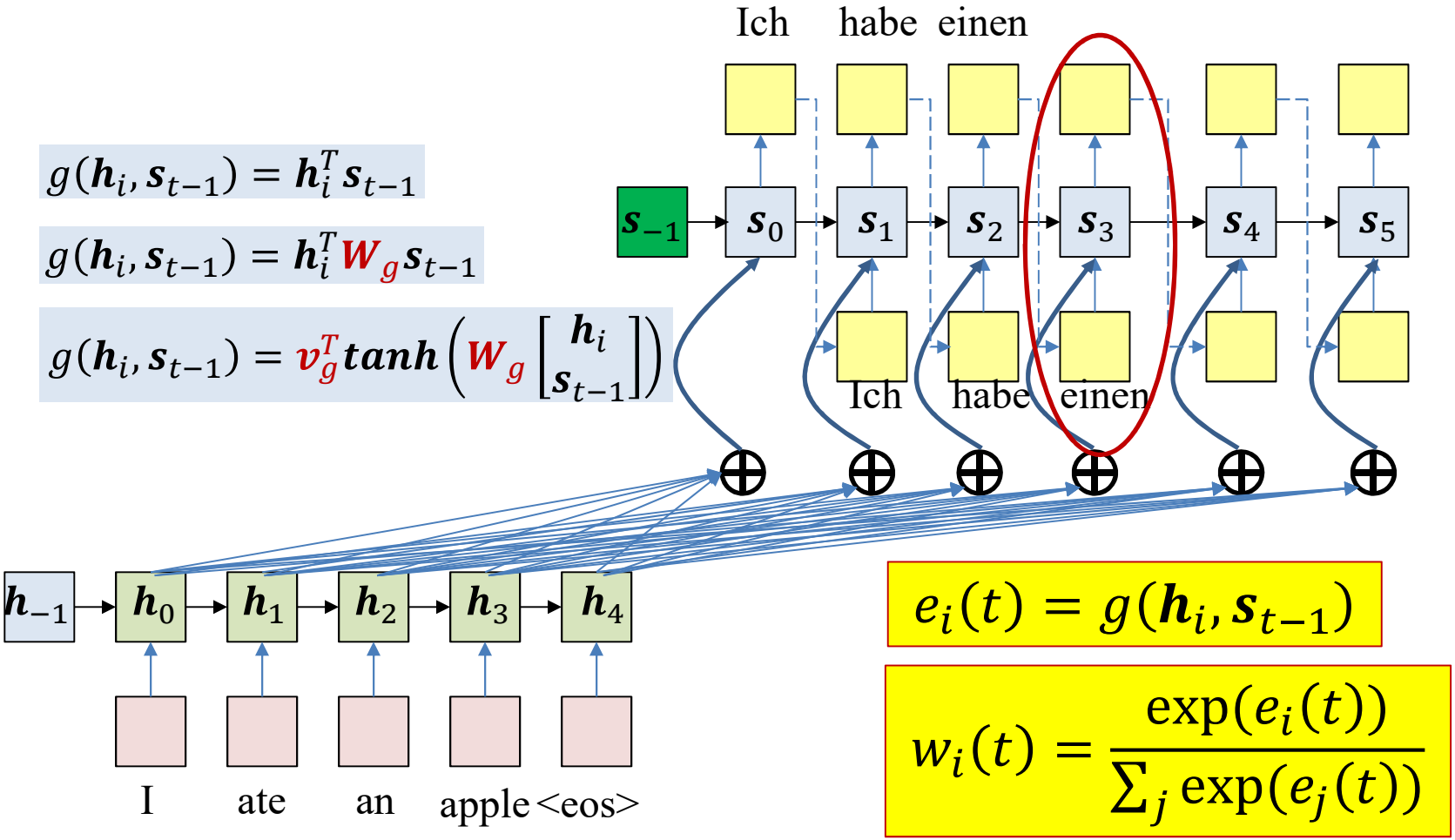
- The weights are a distribution over the input
  - Must automatically highlight the most important input components for any output

Attention models



- "Raw" weight at any time: A function $g()$ that works on the two hidden states
- Actual weight: softmax over raw weights

Attention models



$$g(\boldsymbol{h}_i, \boldsymbol{s}_{t-1}) = \boldsymbol{h}_i^T \boldsymbol{s}_{t-1}$$

$$g(\boldsymbol{h}_i, \boldsymbol{s}_{t-1}) = \boldsymbol{h}_i^T \boldsymbol{W}_g \boldsymbol{s}_{t-1}$$

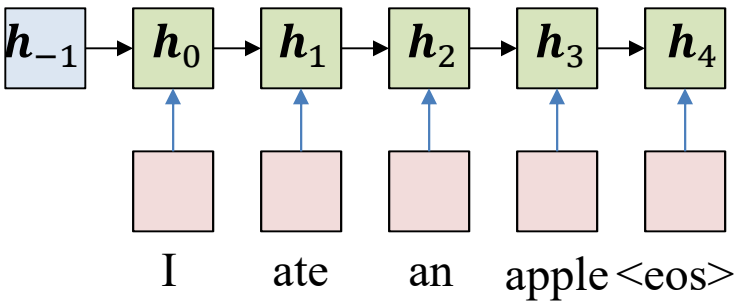
$$g(\boldsymbol{h}_i, \boldsymbol{s}_{t-1}) = \boldsymbol{v}_g^T \tanh\left(\boldsymbol{W}_g \begin{bmatrix} \boldsymbol{h}_i \\ \boldsymbol{s}_{t-1} \end{bmatrix}\right)$$

$$e_i(t) = g(\boldsymbol{h}_i, \boldsymbol{s}_{t-1})$$

$$w_i(t) = \frac{\exp(e_i(t))}{\sum_j \exp(e_j(t))}$$

- Typical options for $g()$…
  - Variables in red are to be learned

Converting an input (forward pass)



- Pass the input through the encoder to produce hidden representations $\boldsymbol{h}_i$

Converting an input (forward pass)

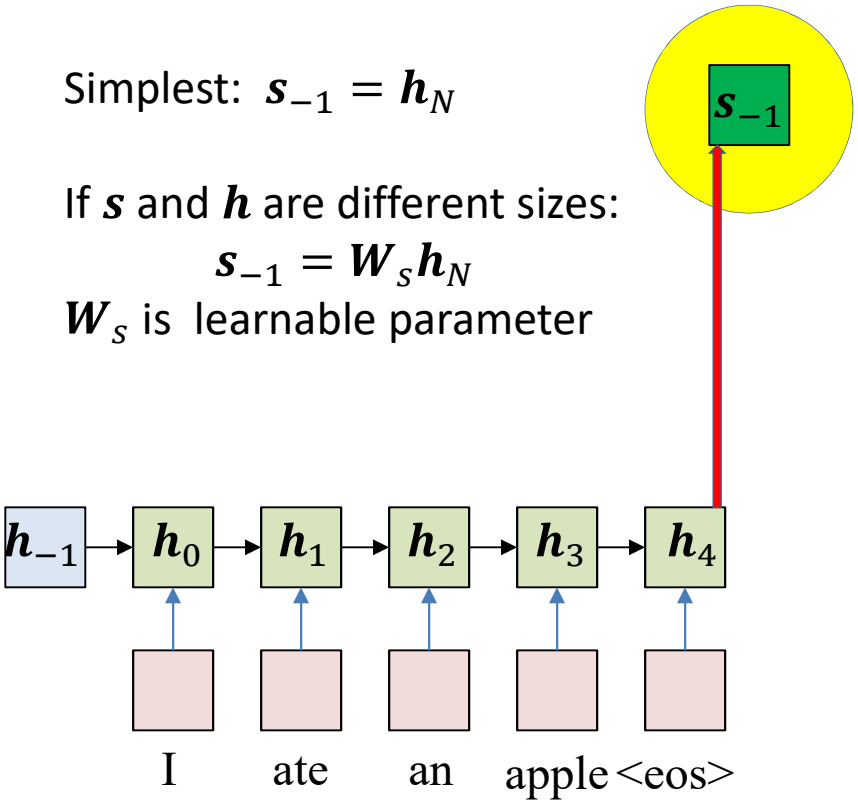
What is this?
Multiple options

Simplest: $\boldsymbol{s_{-1} = h_N}$

If $\boldsymbol{s}$ and $\boldsymbol{h}$ are different sizes:

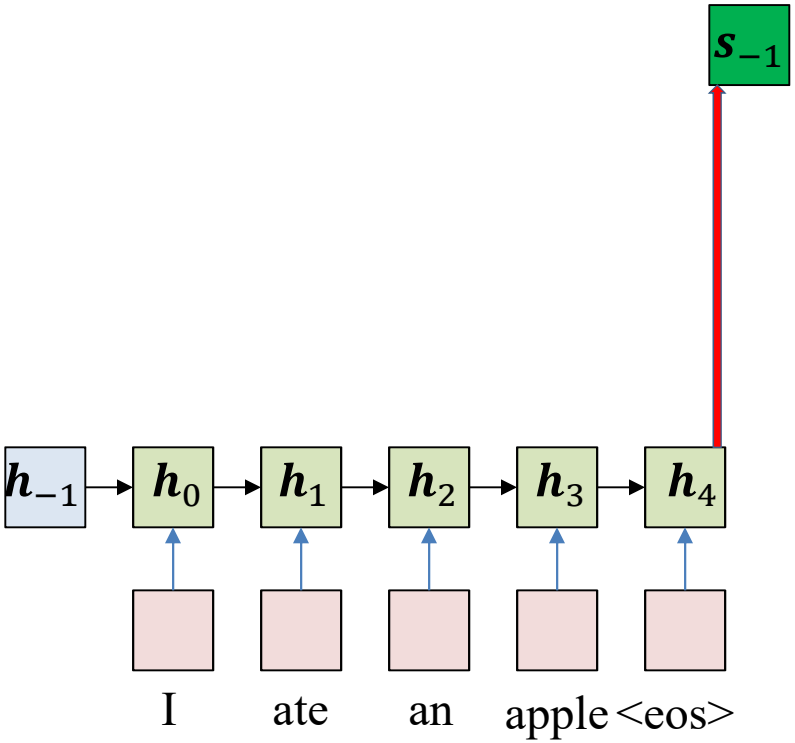
$$\boldsymbol{s_{-1} = W_s h_N}$$

$\boldsymbol{W_s}$ is learnable parameter



- Compute weights for first output

Converting an input (forward pass)



$$g(\boldsymbol{h}_i, \boldsymbol{s}_{-1}) = \boldsymbol{h}_i^T \boldsymbol{W}_g \boldsymbol{s}_{-1}$$

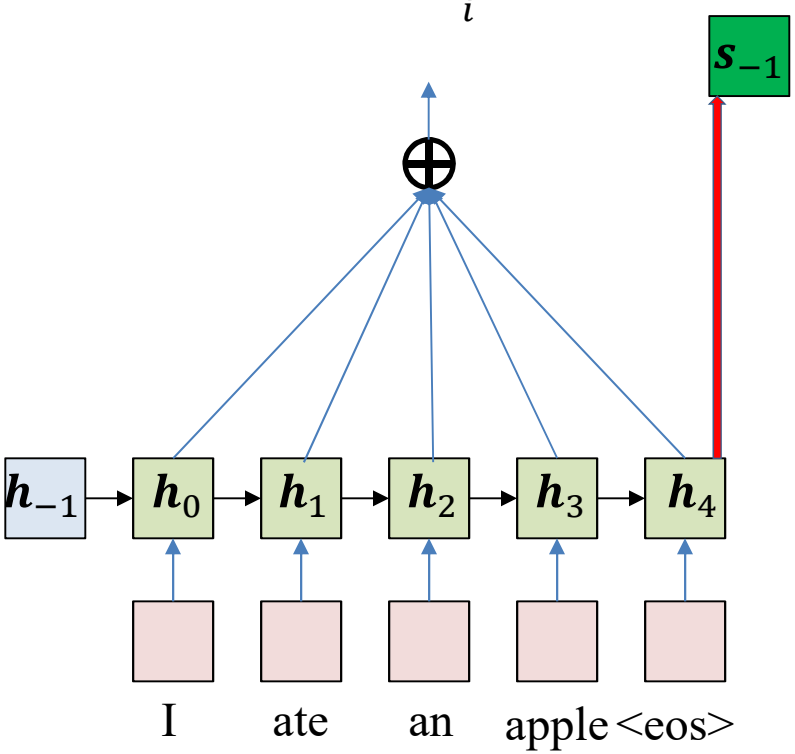
$$e_i(0) = g(\boldsymbol{h}_i, \boldsymbol{s}_{-1})$$

$$w_i(0) = \frac{\exp(e_i(0))}{\sum_j \exp(e_j(0))}$$

- Compute weights (for every $\boldsymbol{h}_i$) for first output

Converting an input (forward pass)

$$z_0 = \sum_i w_i(0) h_i$$



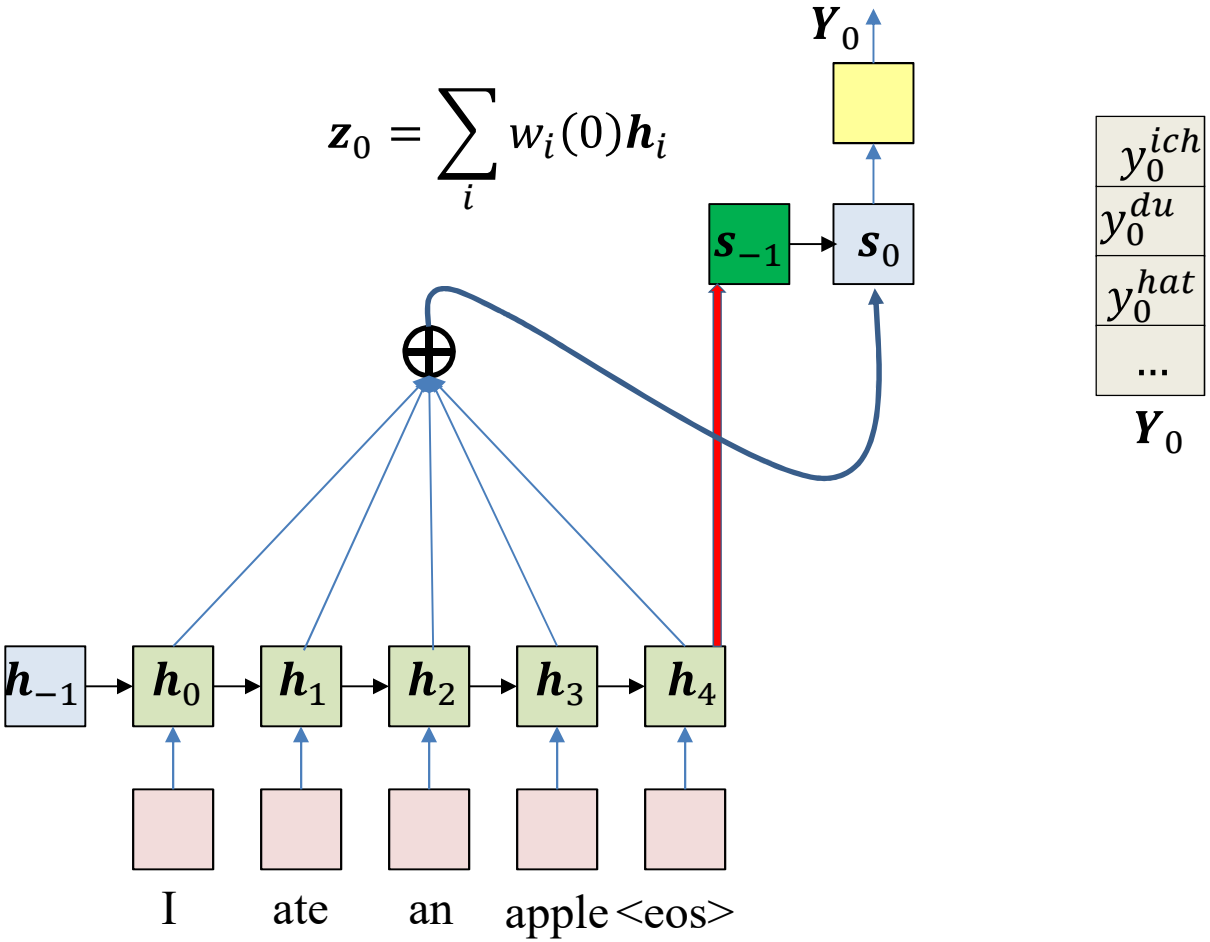
$$g(h_i, s_{-1}) = h_i^T W_g s_{-1}$$

$$e_i(0) = g(h_i, s_{-1})$$

$$w_i(0) = \frac{\exp(e_i(0))}{\sum_j \exp(e_j(0))}$$

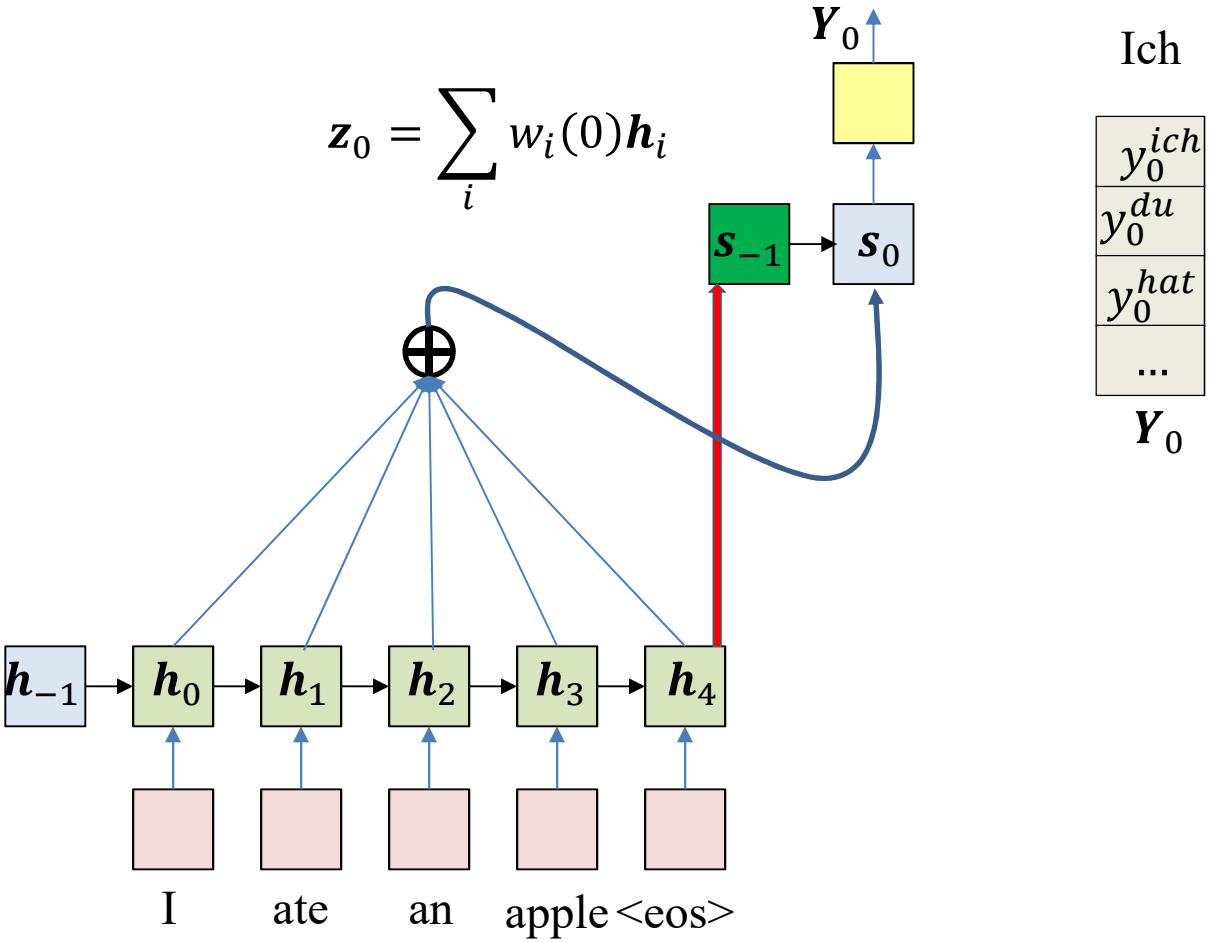
- Compute weights (for every h_i) for first output
- Compute weighted combination of hidden values

Converting an input (forward pass)

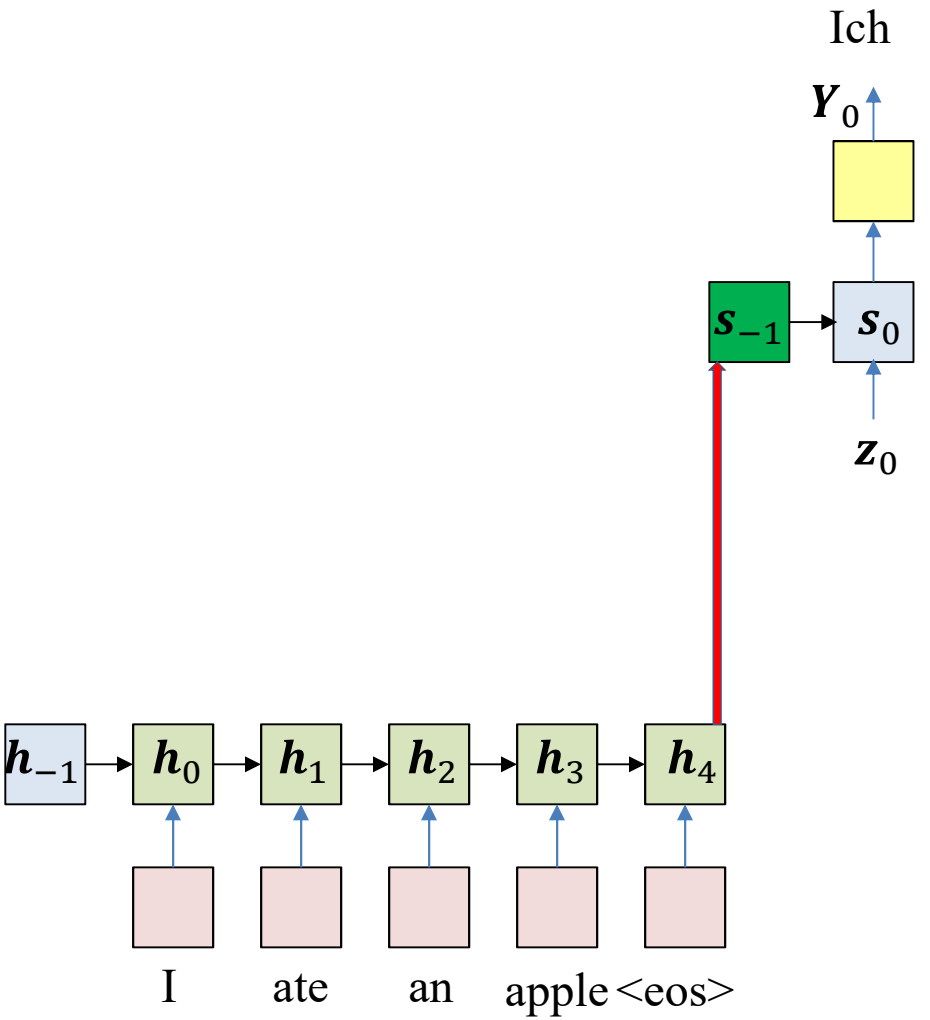


- Produce the first output
  - Will be distribution over words

Converting an input (forward pass)



- Produce the first output
  - Will be distribution over words
  - Draw a word from the distribution

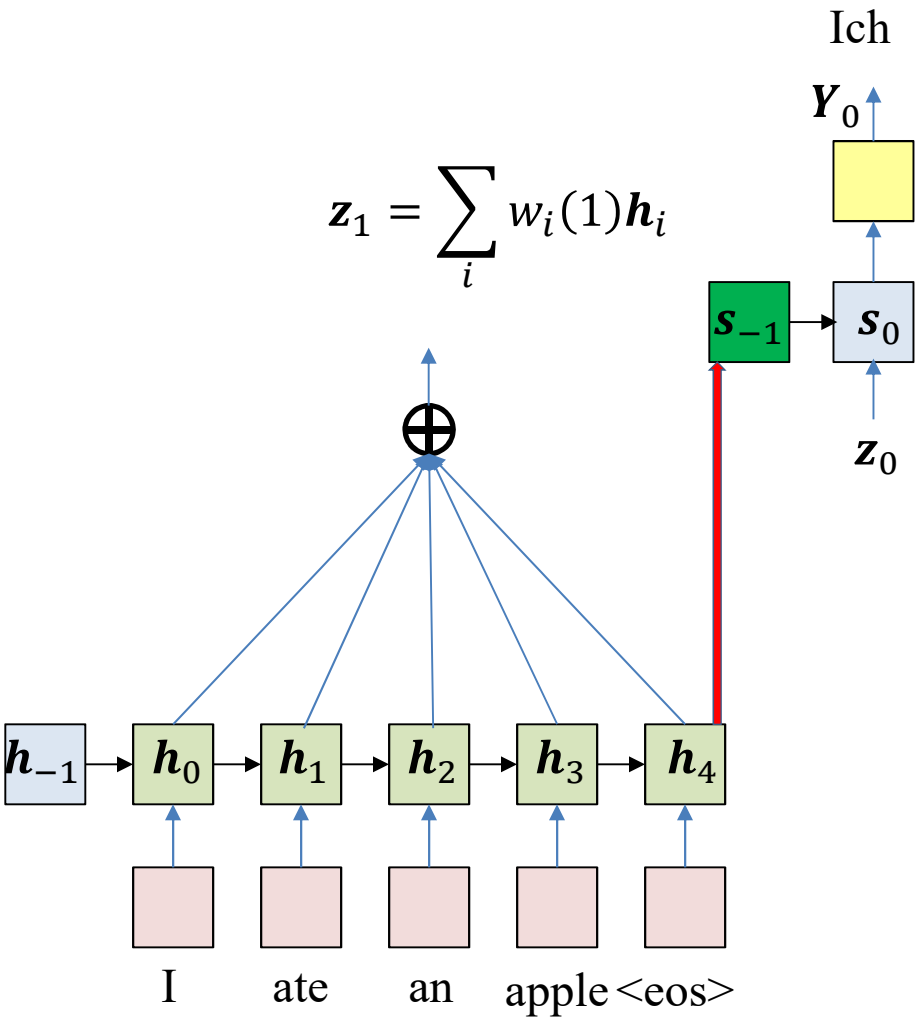


$$g(\boldsymbol{h}_i, \boldsymbol{s}_0) = \boldsymbol{h}_i^T \boldsymbol{W}_g \boldsymbol{s}_0$$

$$e_i(1) = g(\boldsymbol{h}_i, \boldsymbol{s}_0)$$

$$w_i(1) = \frac{\exp(e_i(1))}{\sum_j \exp(e_j(1))}$$

- Compute the weights for all instances for time = 1

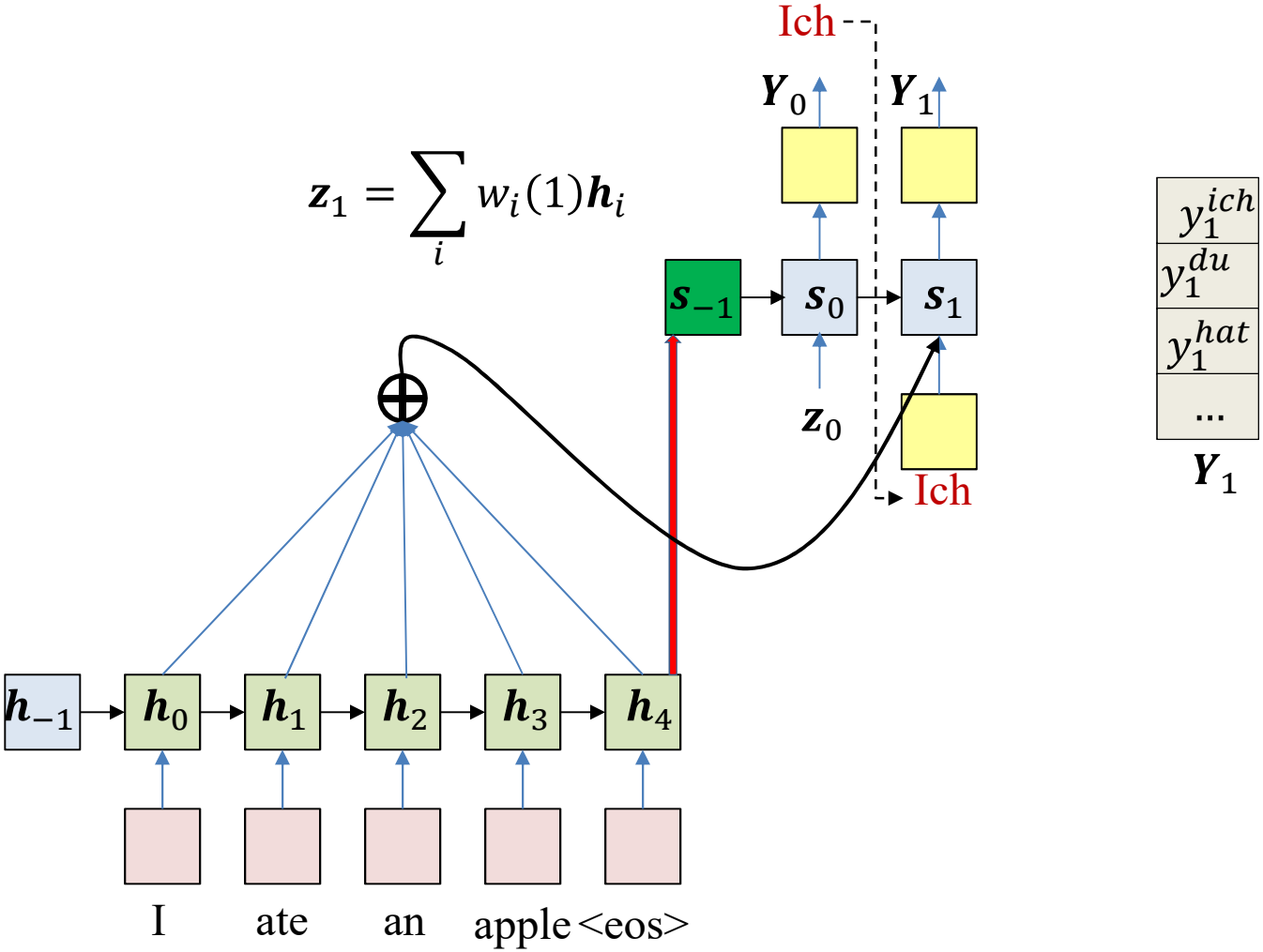


$$g(\boldsymbol{h}_i, \boldsymbol{s}_0) = \boldsymbol{h}_i^T \boldsymbol{W}_g \boldsymbol{s}_0$$

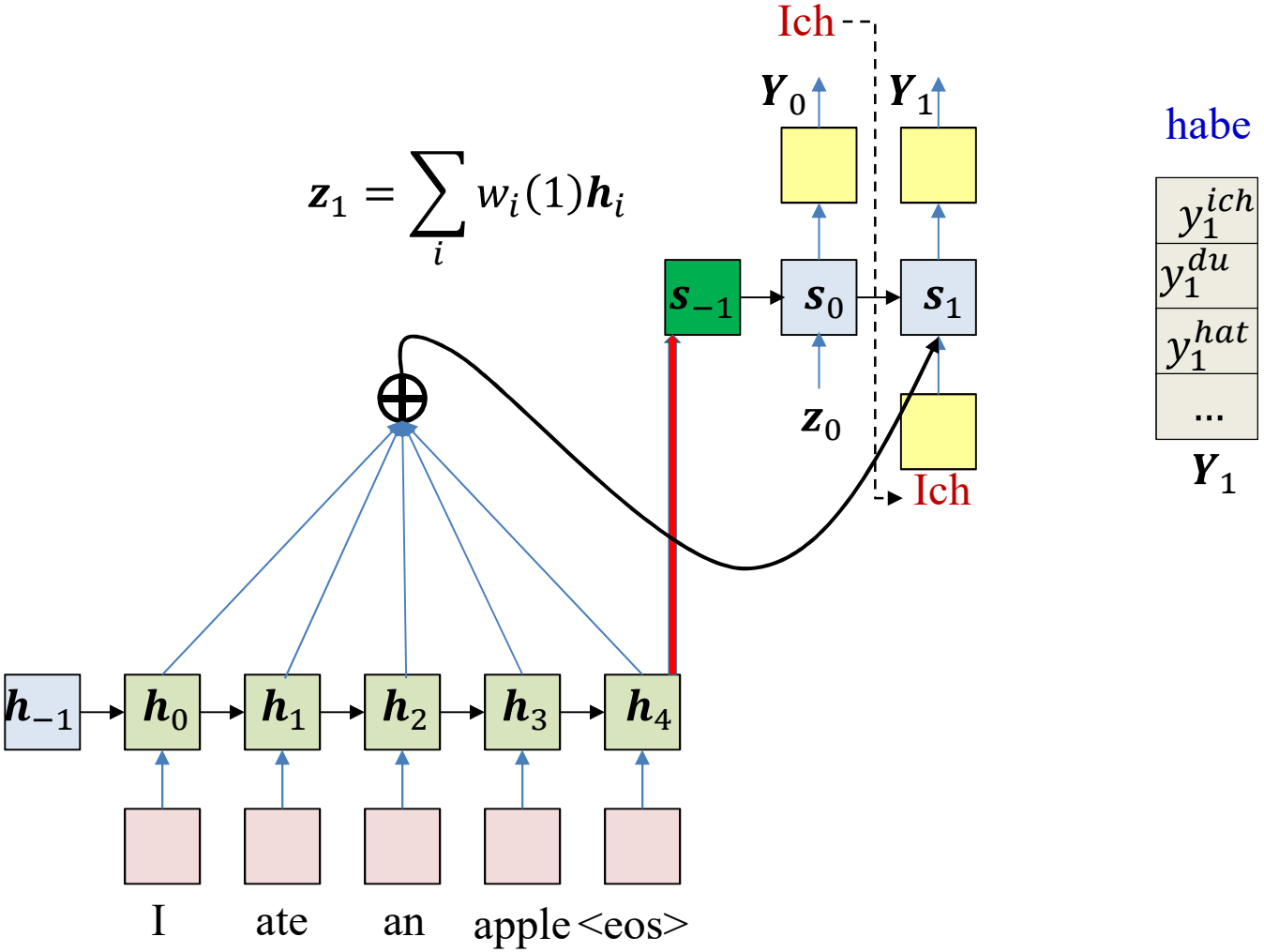
$$e_i(1) = g(\boldsymbol{h}_i, \boldsymbol{s}_0)$$

$$w_i(1) = \frac{\exp(e_i(1))}{\sum_j \exp(e_j(1))}$$

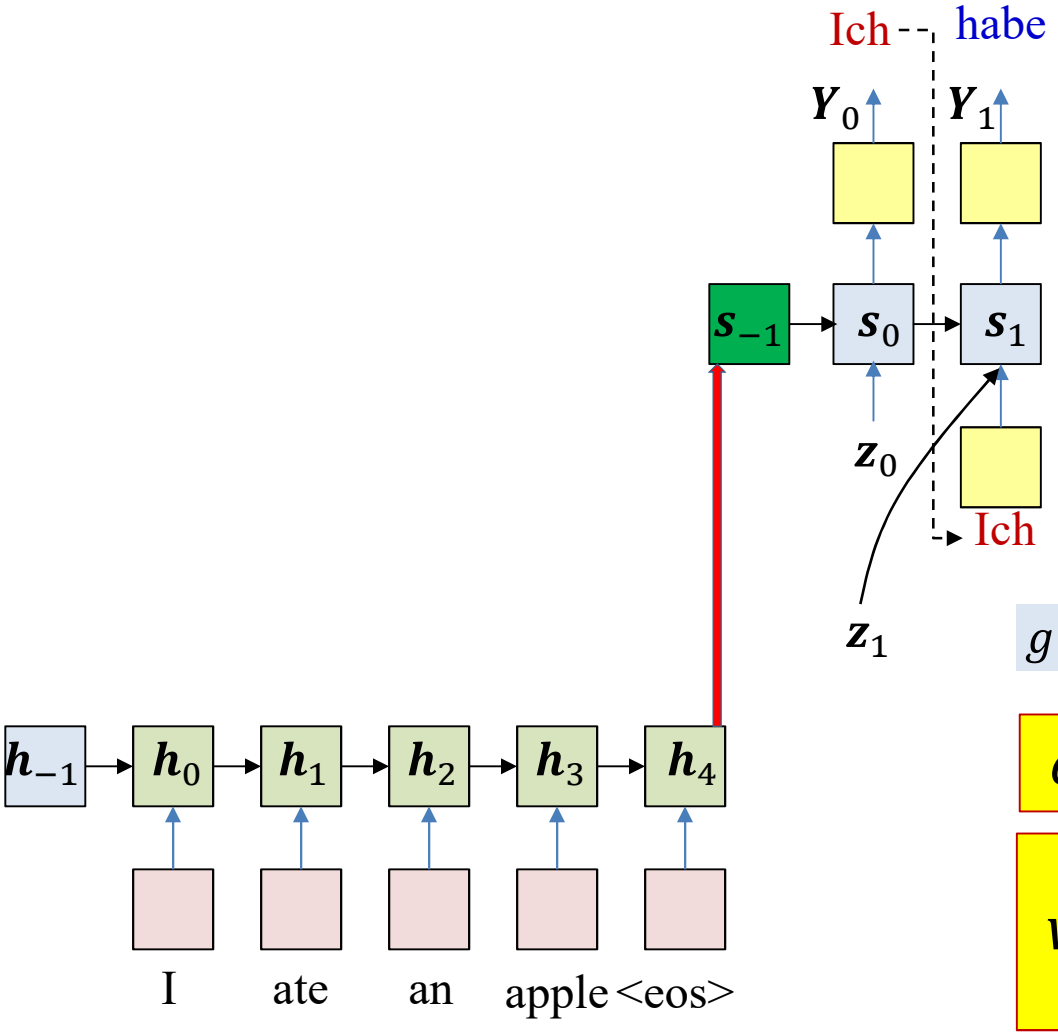
- Compute the weighted sum of hidden input values at t=1



- Compute the output at t=1
  - Will be a probability distribution over words



- Draw a word from the output distribution at t=1

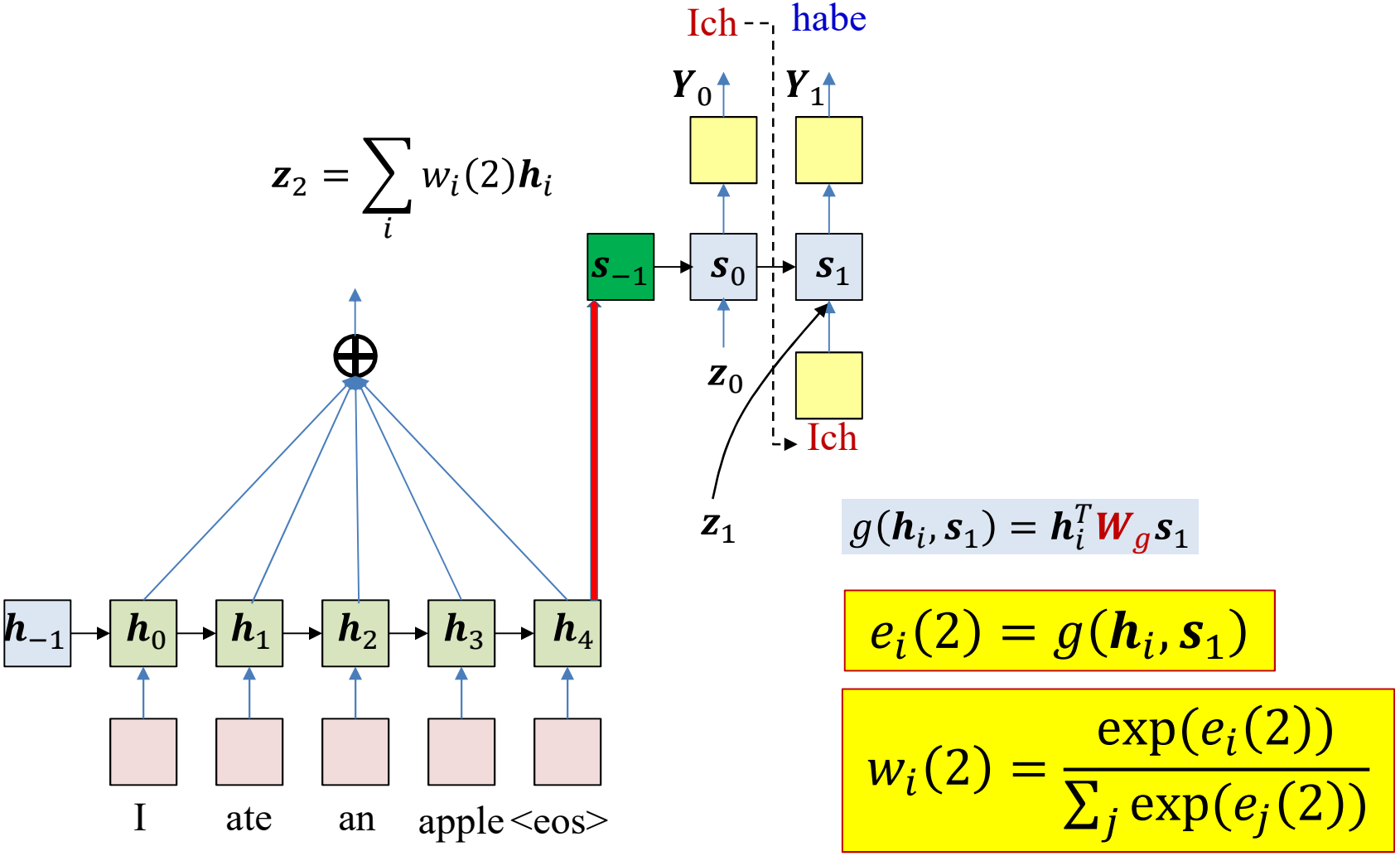


$$g(\boldsymbol{h}_i, \boldsymbol{s}_1) = \boldsymbol{h}_i^T \boldsymbol{W}_g \boldsymbol{s}_1$$

$$e_i(2) = g(\boldsymbol{h}_i, \boldsymbol{s}_1)$$

$$w_i(2) = \frac{\exp(e_i(2))}{\sum_j \exp(e_j(2))}$$

- Compute the weights for all instances for time = 2

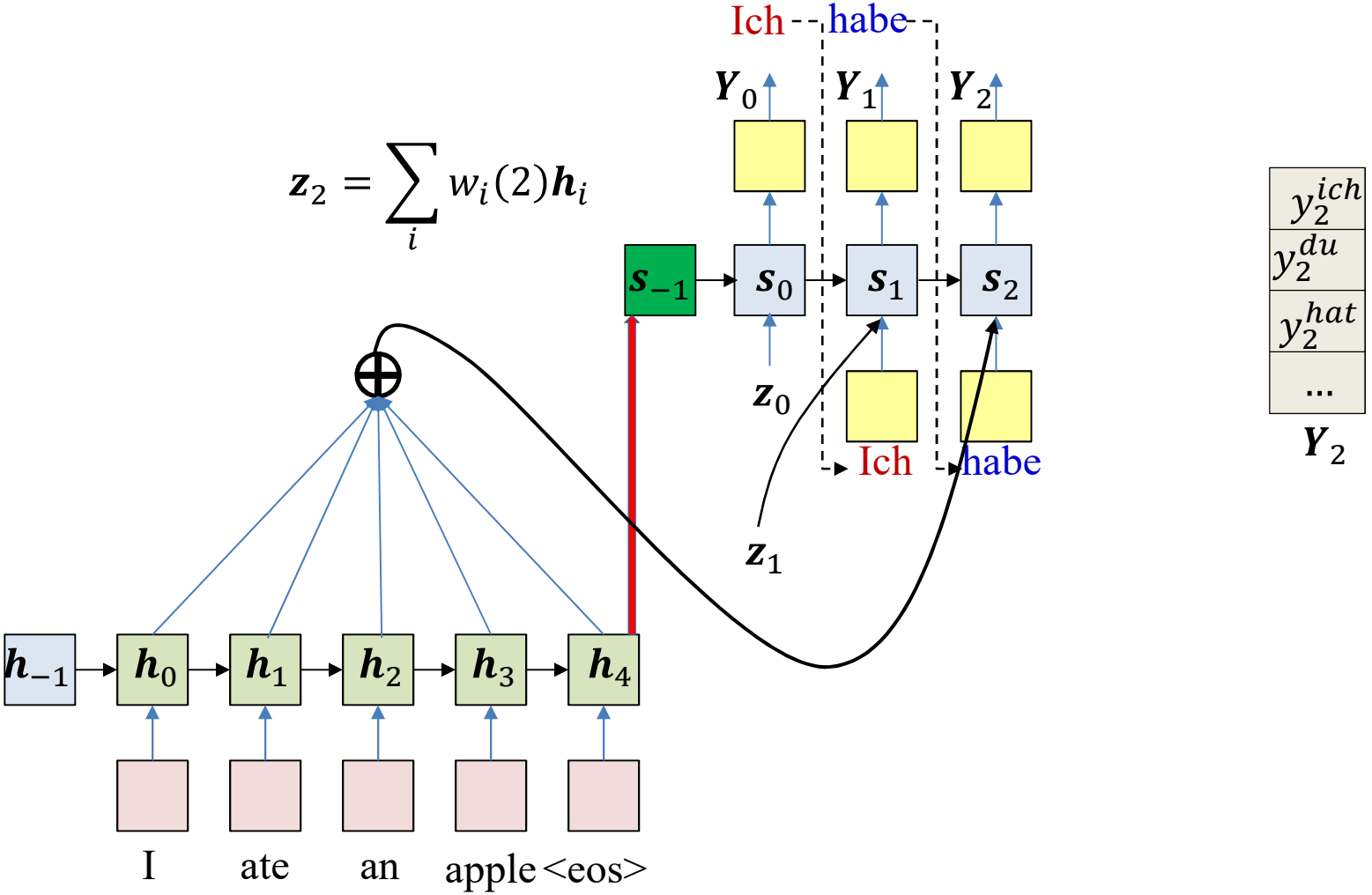


$$g(\boldsymbol{h}_i, \boldsymbol{s}_1) = \boldsymbol{h}_i^T \boldsymbol{W}_g \boldsymbol{s}_1$$

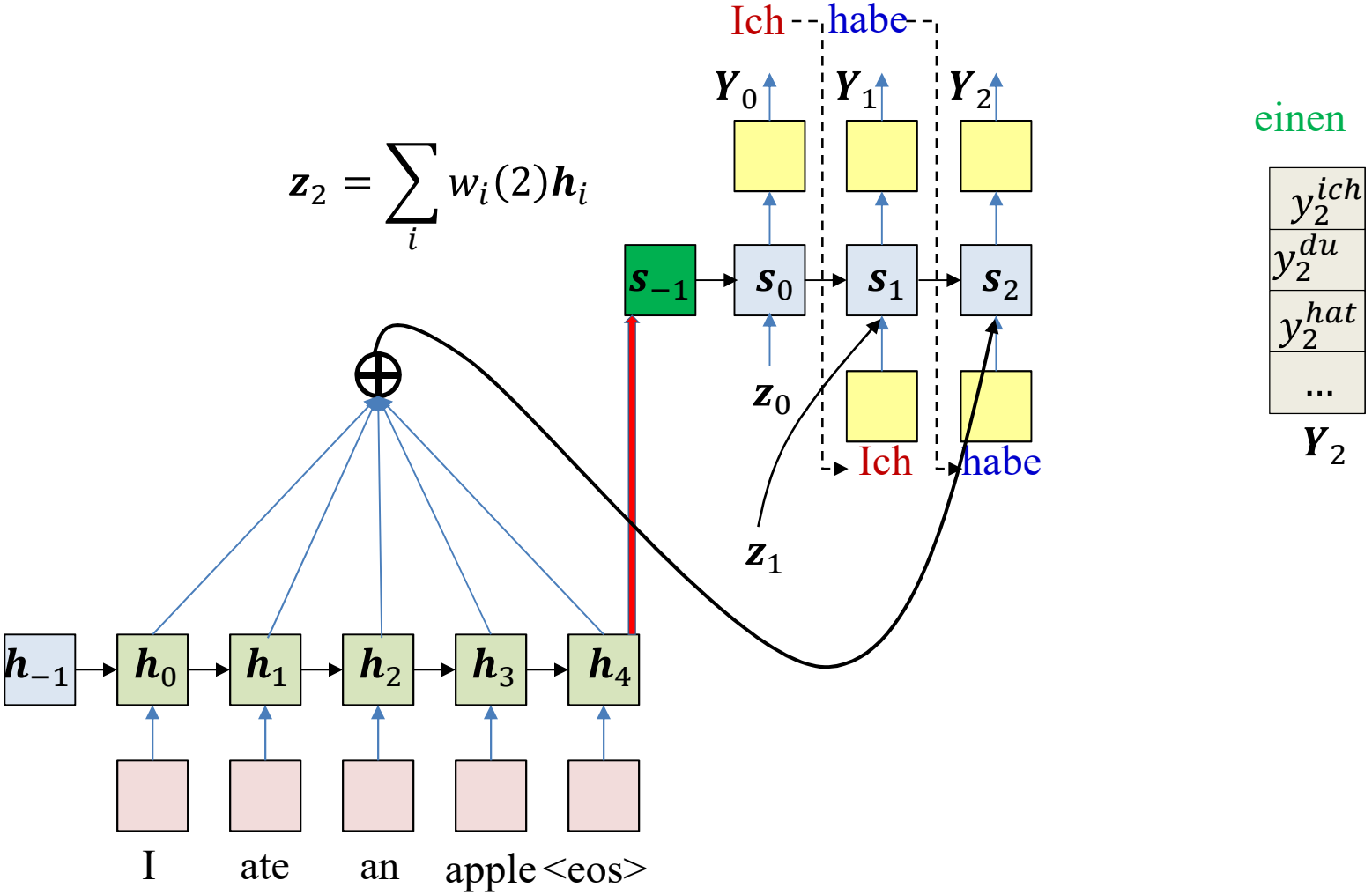
$$e_i(2) = g(\boldsymbol{h}_i, \boldsymbol{s}_1)$$

$$w_i(2) = \frac{\exp(e_i(2))}{\sum_j \exp(e_j(2))}$$

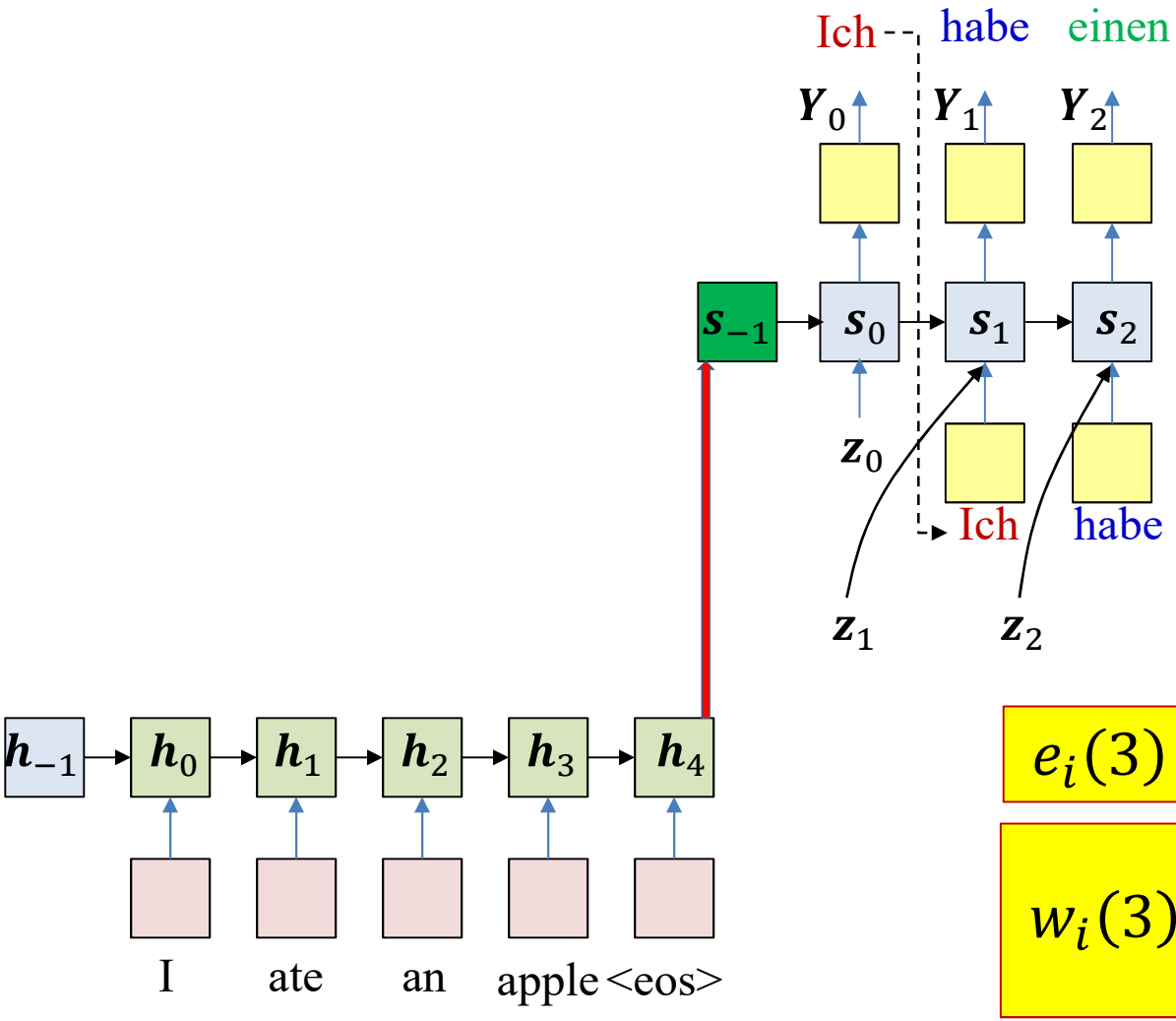
- Compute the weighted sum of hidden input values at t=2



- Compute the output at t=2
  - Will be a probability distribution over words



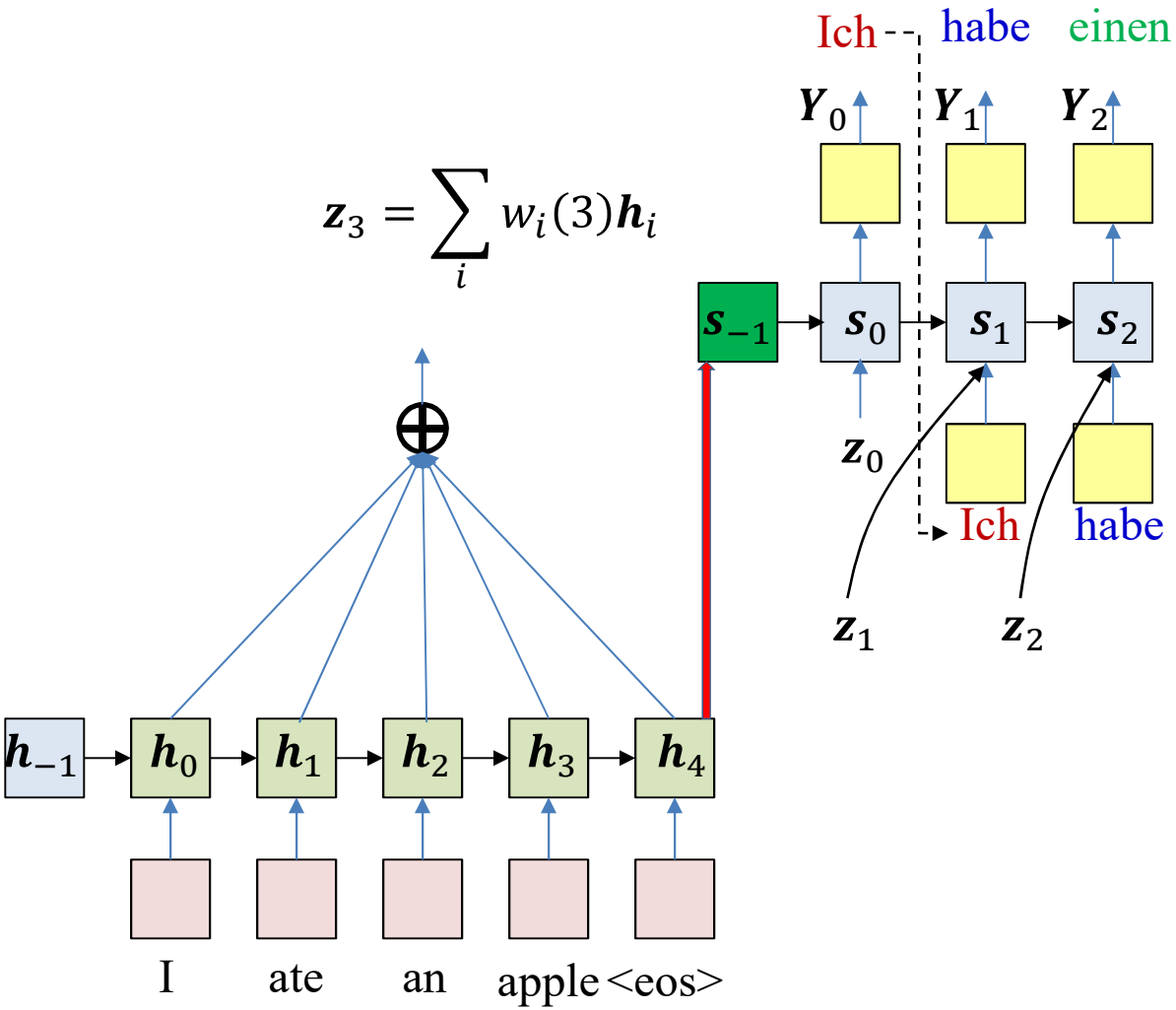
- Draw a word from the distribution



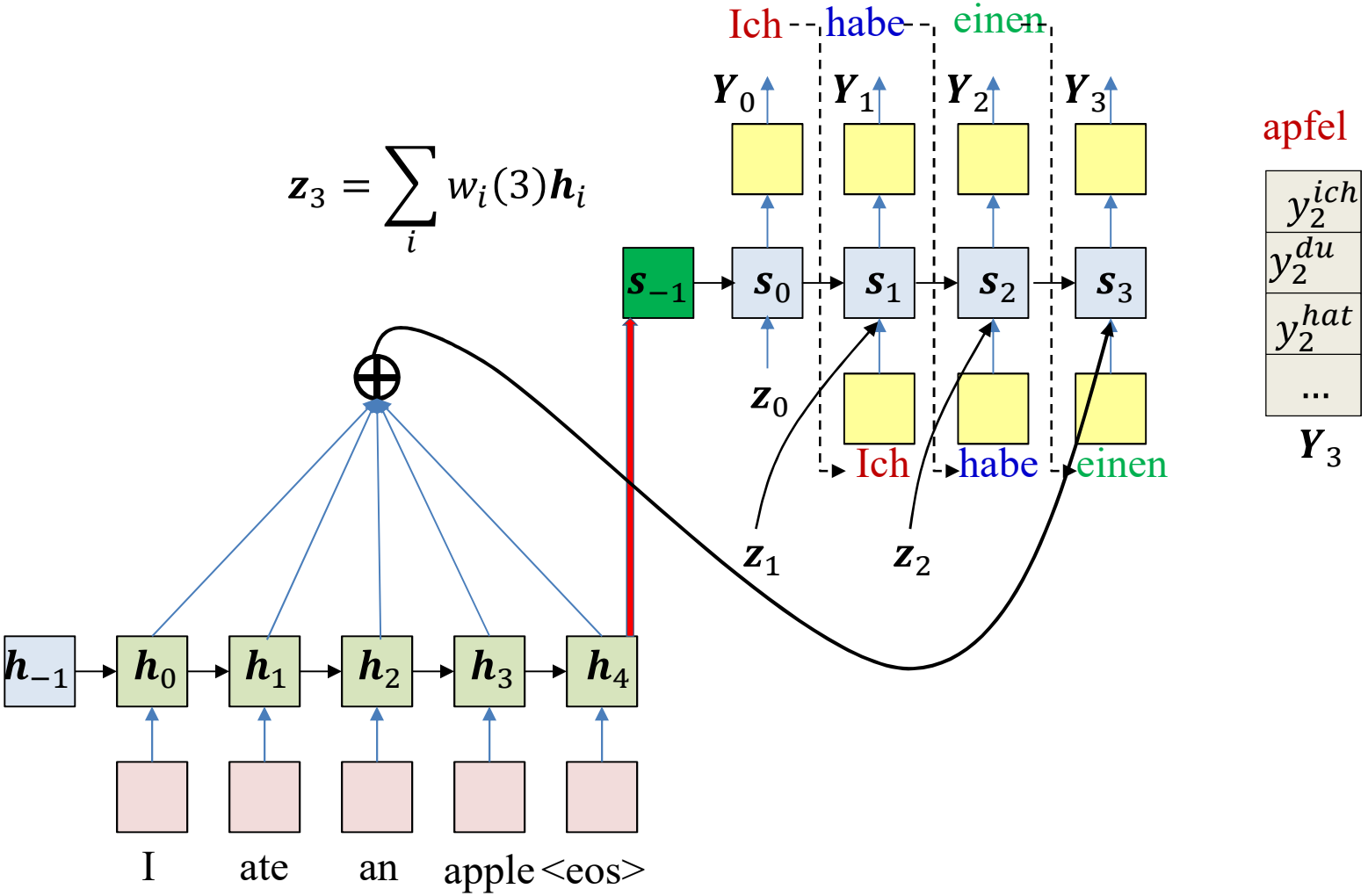
$$e_i(3) = g(\boldsymbol{h}_i, \boldsymbol{s}_2)$$

$$w_i(3) = \frac{\exp(e_i(3))}{\sum_j \exp(e_j(3))}$$

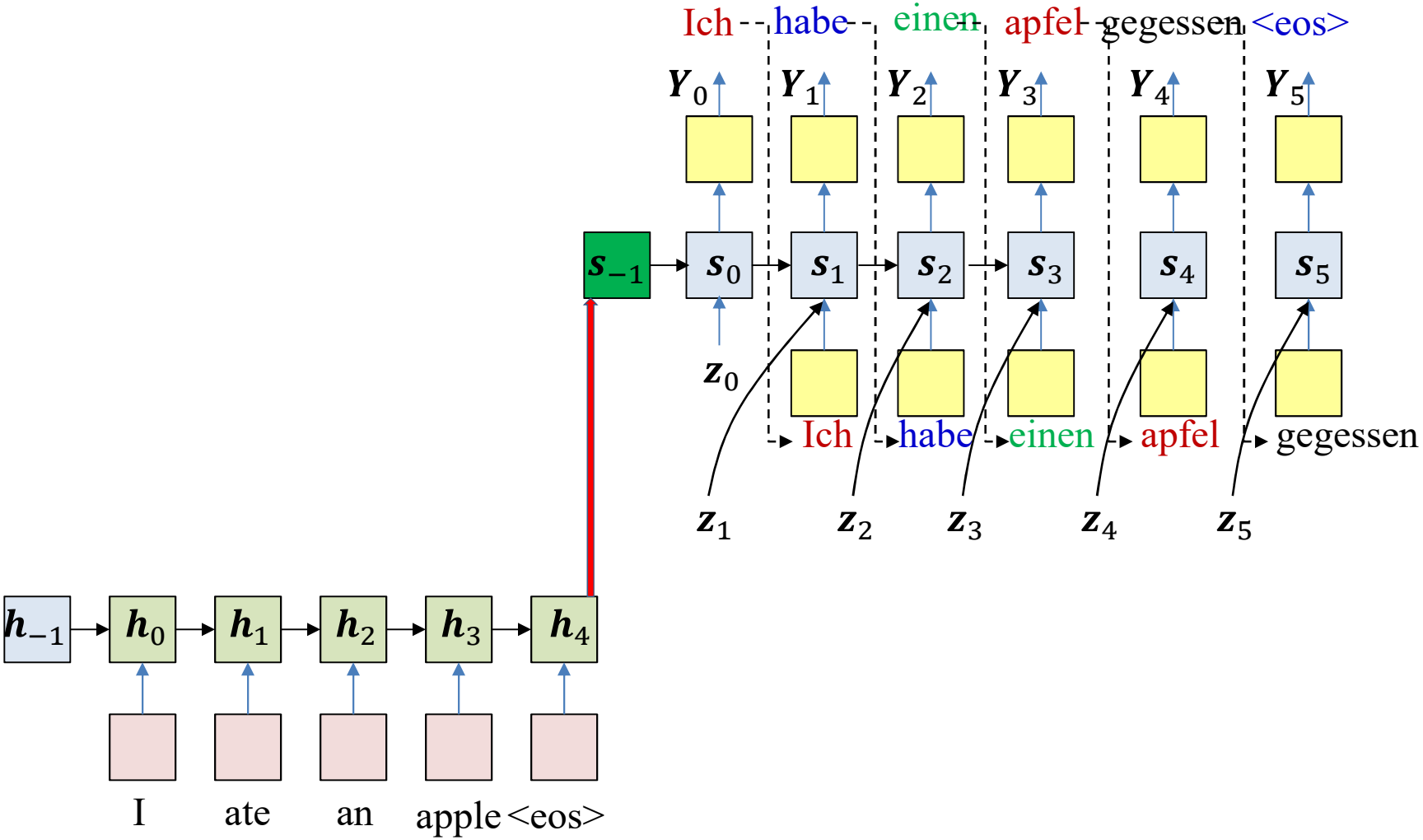
- Compute the weights for all instances for time = 3



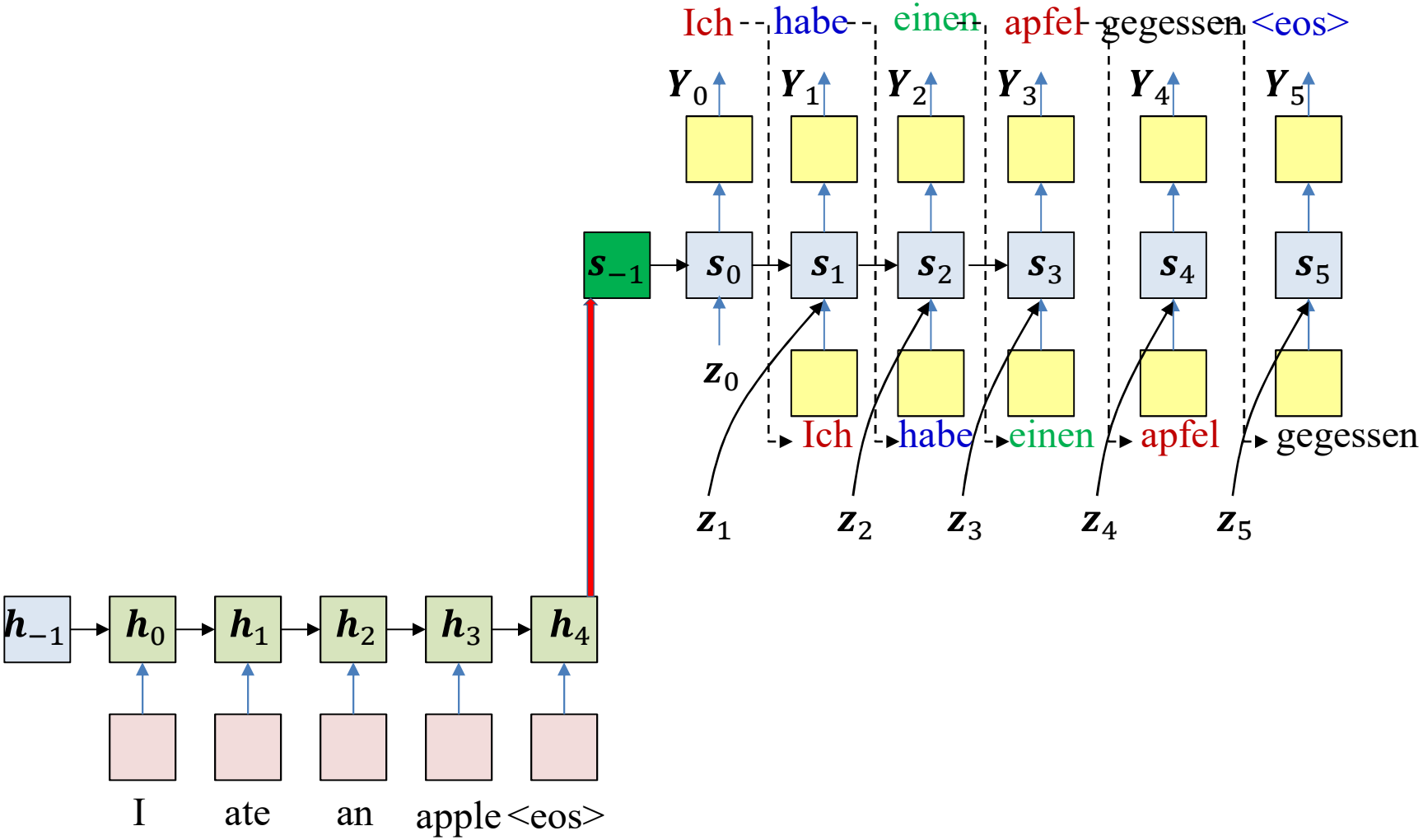
- Compute the weighted sum of hidden input values at t=3



- Compute the output at t=3
  - Will be a probability distribution over words
  - Draw a word from the distribution



- Continue the process until an end-of-sequence symbol is produced

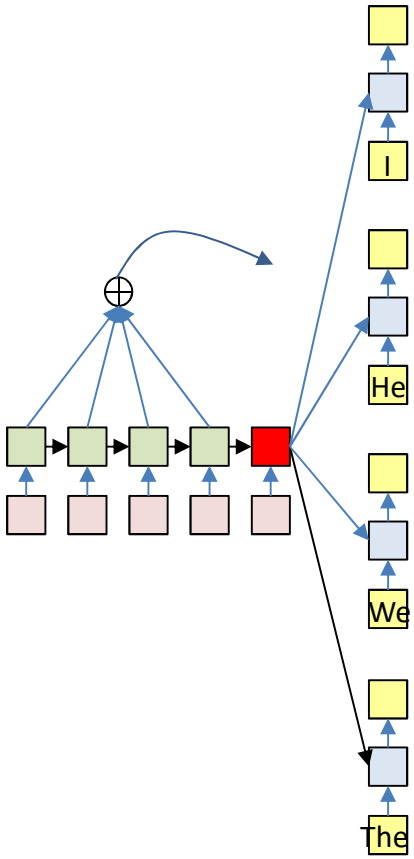


- As before, the objective of drawing: Produce the most likely output (that ends in an <eos>)

$$\underset{o_1,\ldots,o_L}{\operatorname{argmax}} y_1^{o_1} y_1^{o_2} \ldots y_1^{o_L}$$

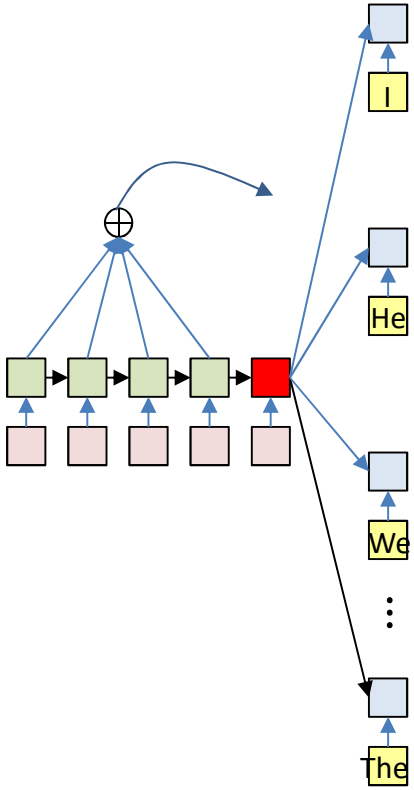
- Simply selecting the most likely symbol at each time may result in suboptimal output

Solution: Multiple choices



- Retain all choices and *fork* the network
  - With every possible word as input

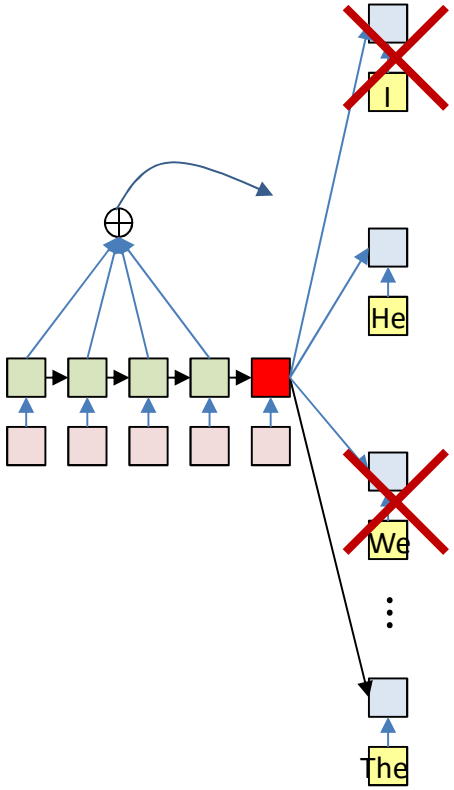
To prevent blowup: Prune



$$Top_K\ P(O_1|I_1, \ldots, I_N)$$

- **Prune**
  - At each time, retain only the top K scoring forks

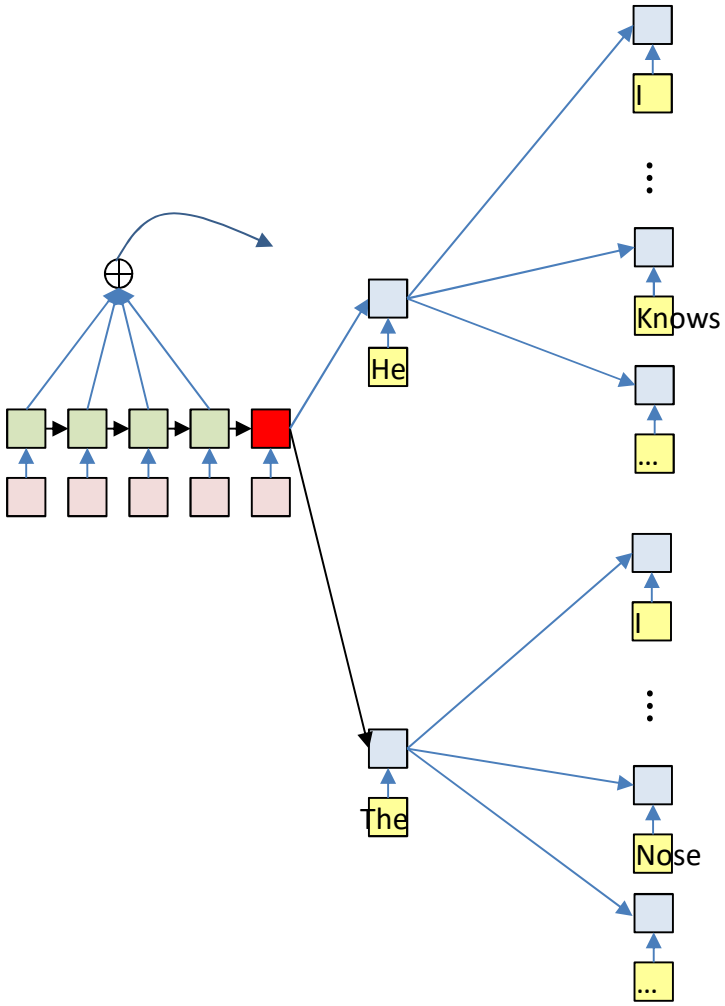
To prevent blowup: Prune



$$Top_K\ P(O_1|I_1, \ldots, I_N)$$

- **Prune**
  - At each time, retain only the top K scoring forks

Decoding



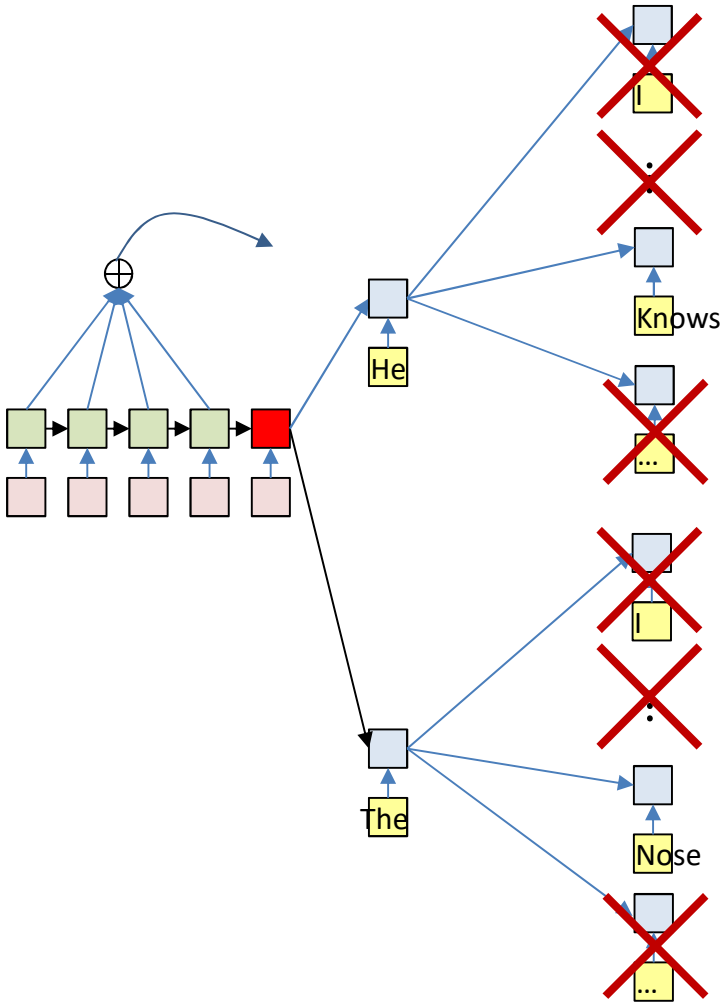
Note: based on product

$$Top_K\ P(O_2 O_1 | I_1, \ldots, I_N)$$

$$= Top_K\ P(O_2 | O_1, I_1, \ldots, I_N) P(O_1 | I_1, \ldots, I_N)$$

- At each time, retain only the top K scoring forks

Decoding



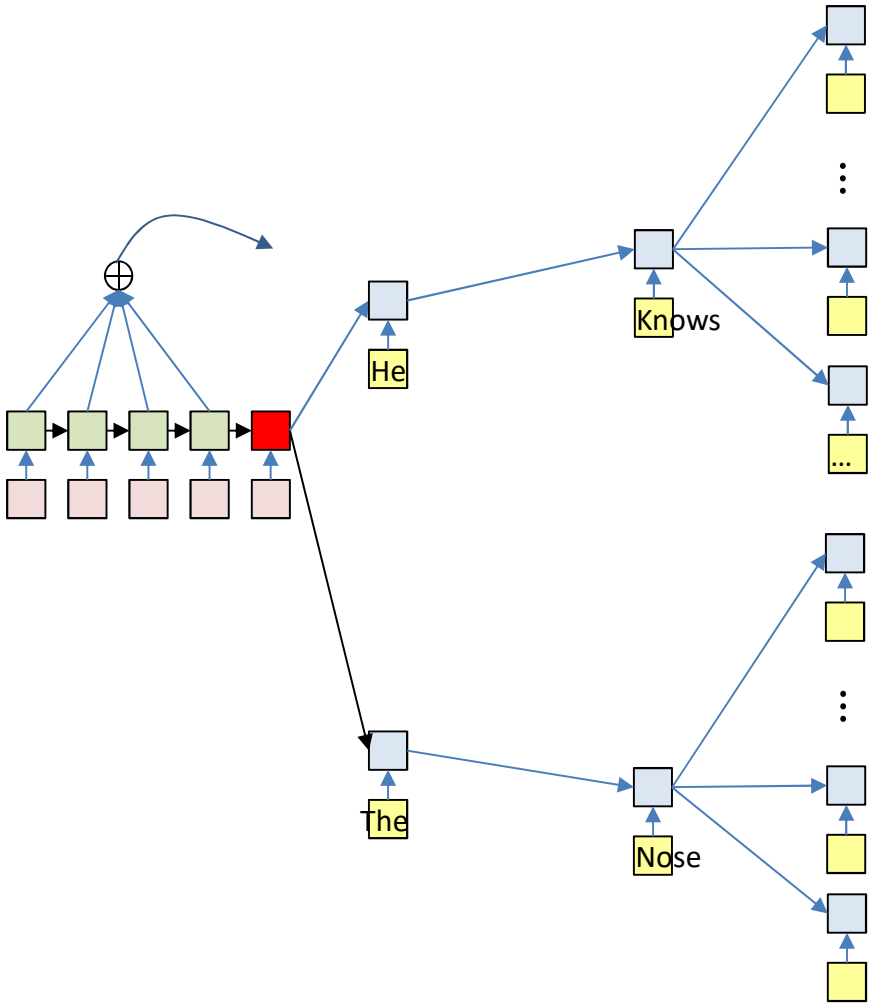
Note: based on product

$$Top_K\ P(O_2 O_1 | I_1, \ldots, I_N)$$

$$= Top_K\ P(O_2 | O_1, I_1, \ldots, I_N) P(O_1 | I_1, \ldots, I_N)$$

- At each time, retain only the top K scoring forks

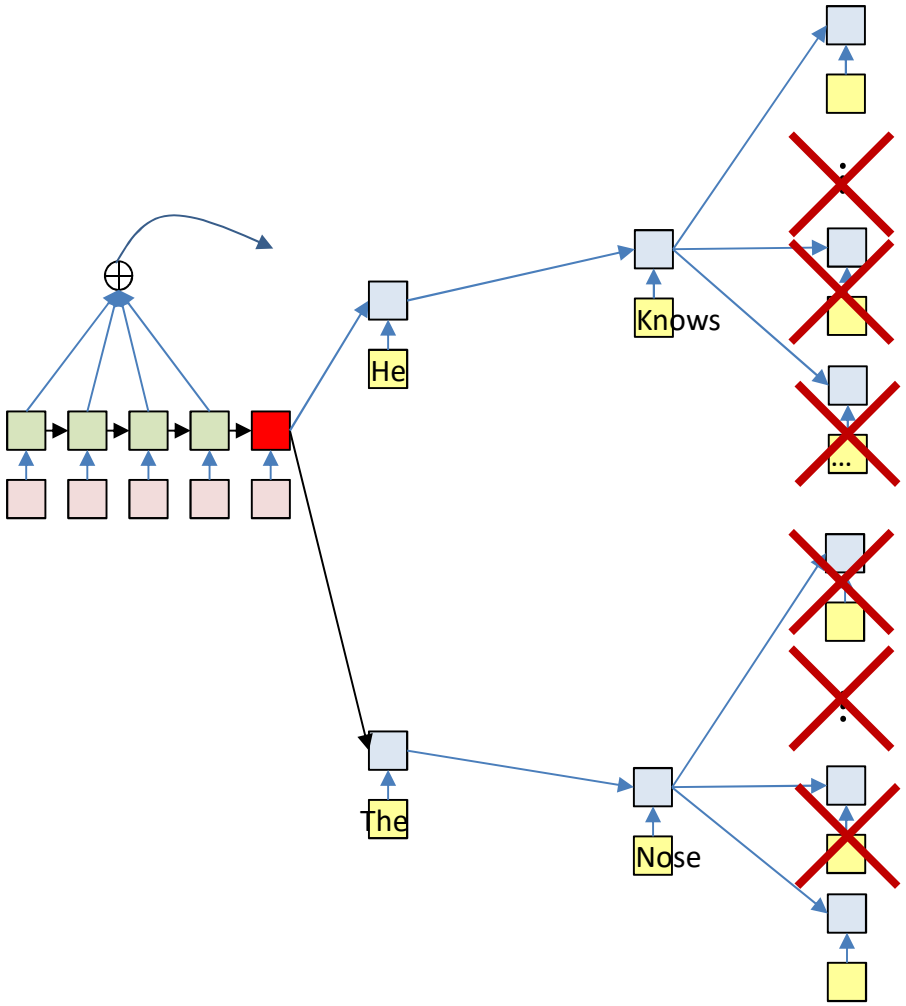
Decoding



$$= Top_K P(O_2|O_1, I_1, \ldots, I_N) \times P(O_2|O_1, I_1, \ldots, I_N) \times P(O_1|I_1, \ldots, I_N)$$

- At each time, retain only the top K scoring forks

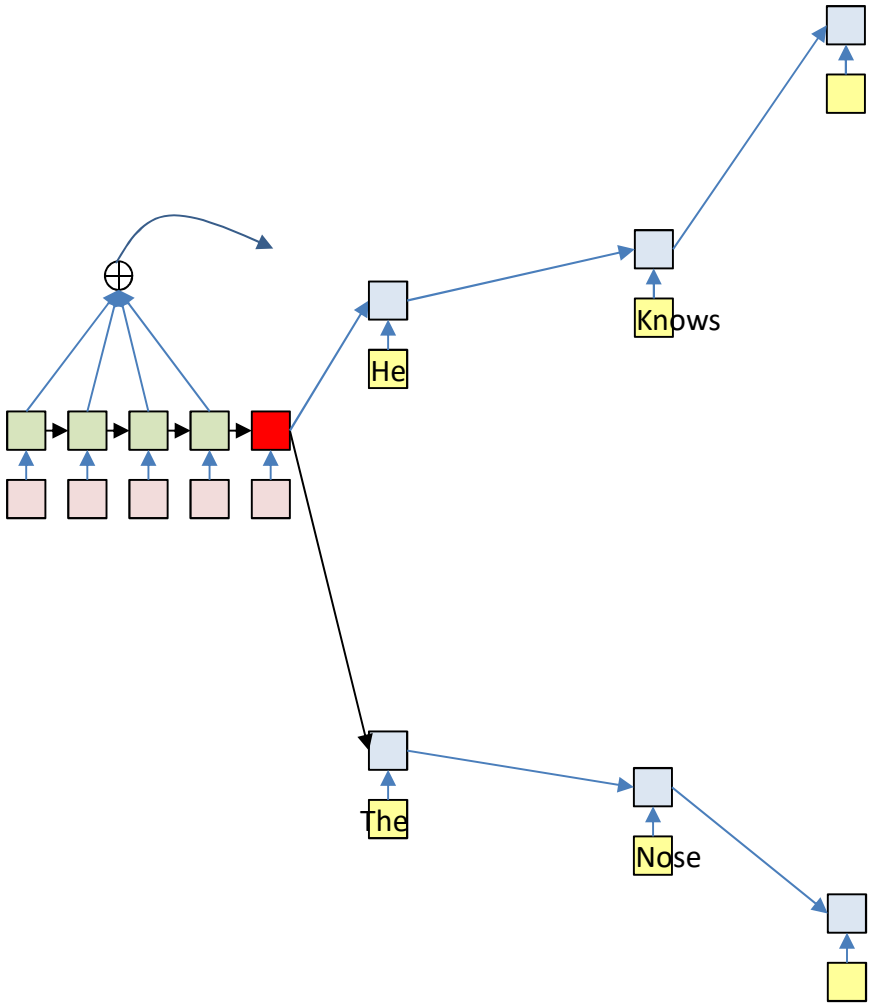
Decoding



$$= Top_K P(O_2|O_1, I_1, \ldots, I_N) \times P(O_2|O_1, I_1, \ldots, I_N) \times P(O_1|I_1, \ldots, I_N)$$

- At each time, retain only the top K scoring forks

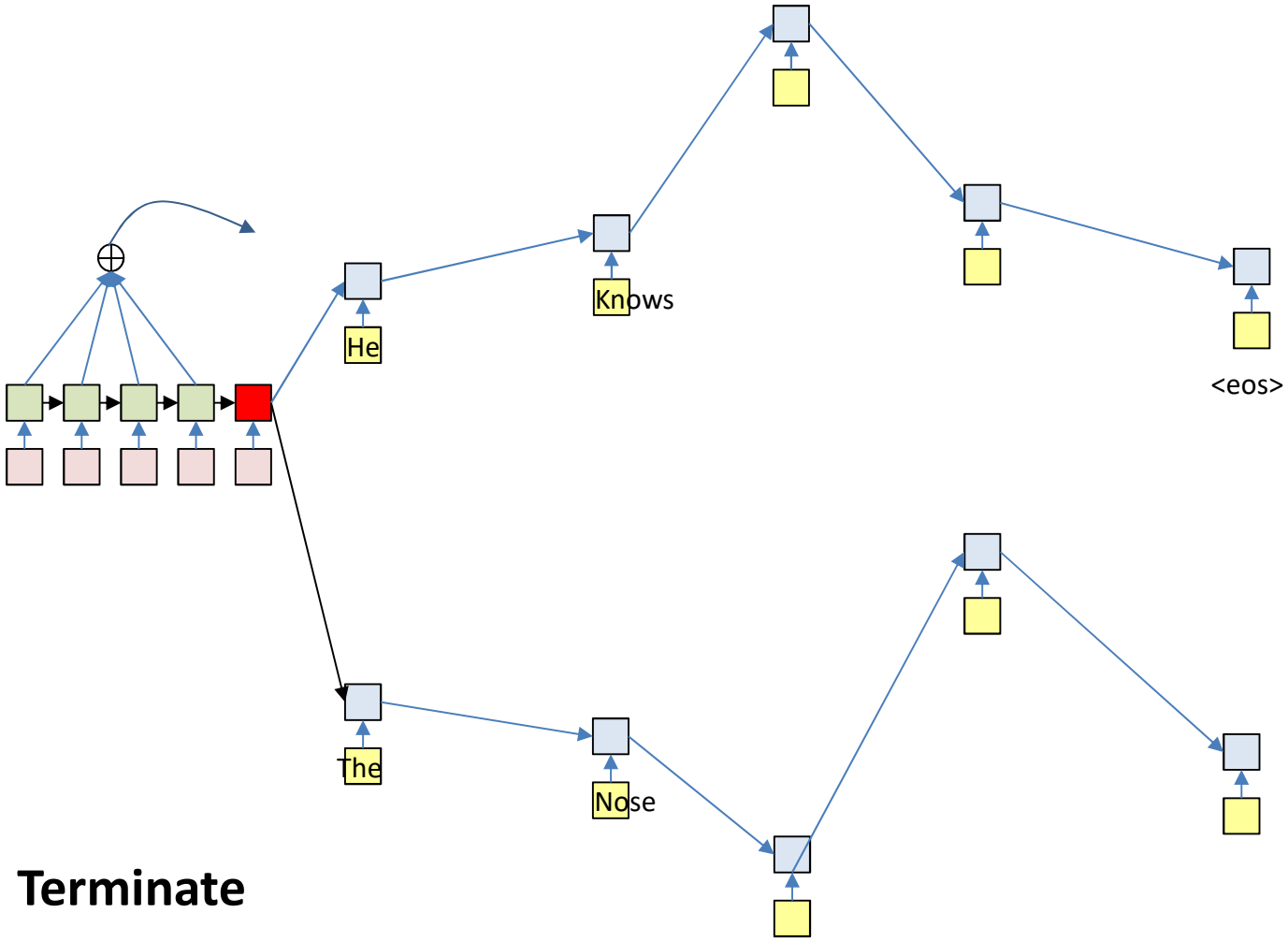
Decoding



$$Top_K \prod_{t=1}^{n} P(O_n | O_1, \ldots, O_{n-1}, I_1, \ldots, I_N)$$

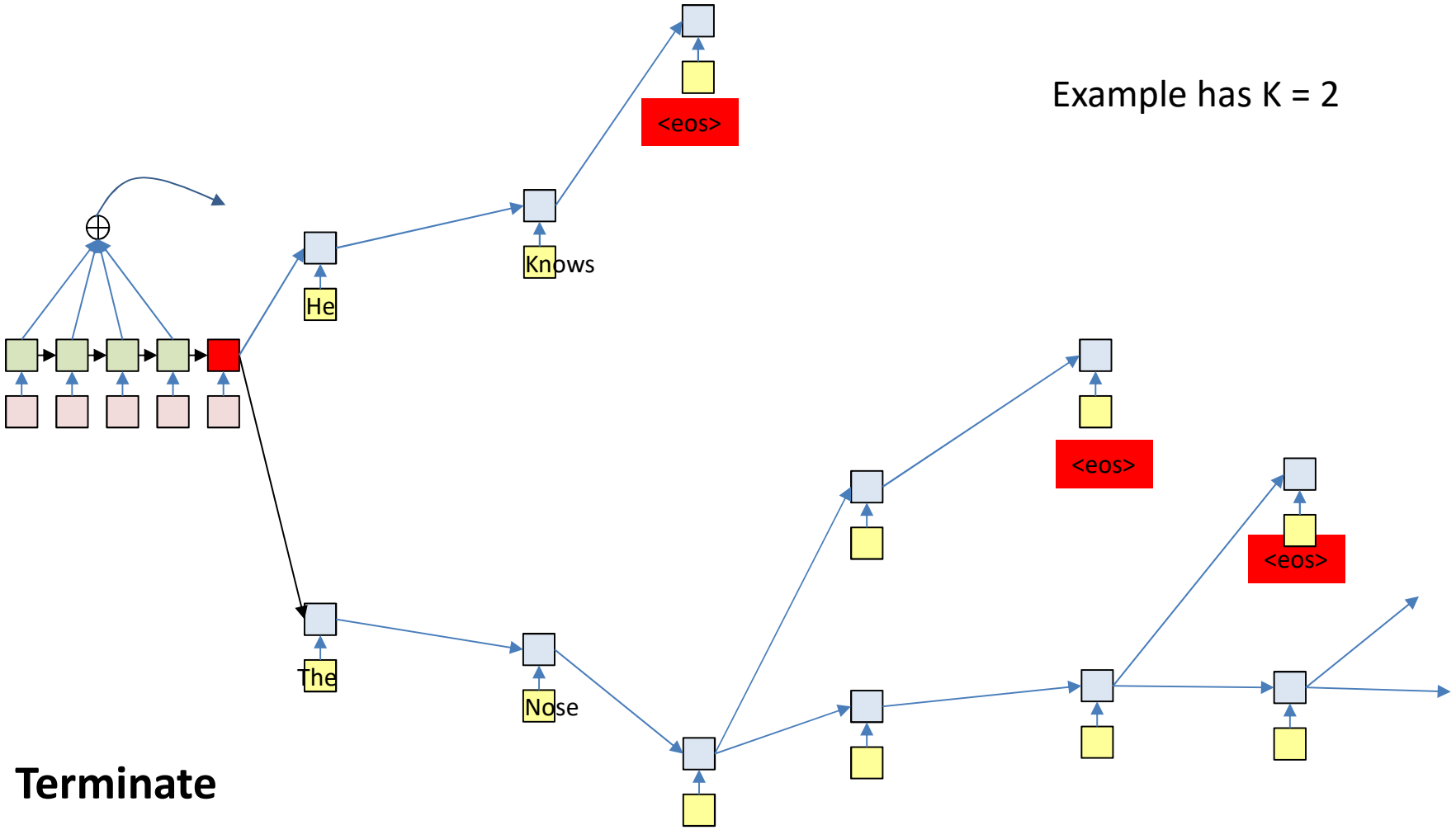
- At each time, retain only the top K scoring forks

Terminate



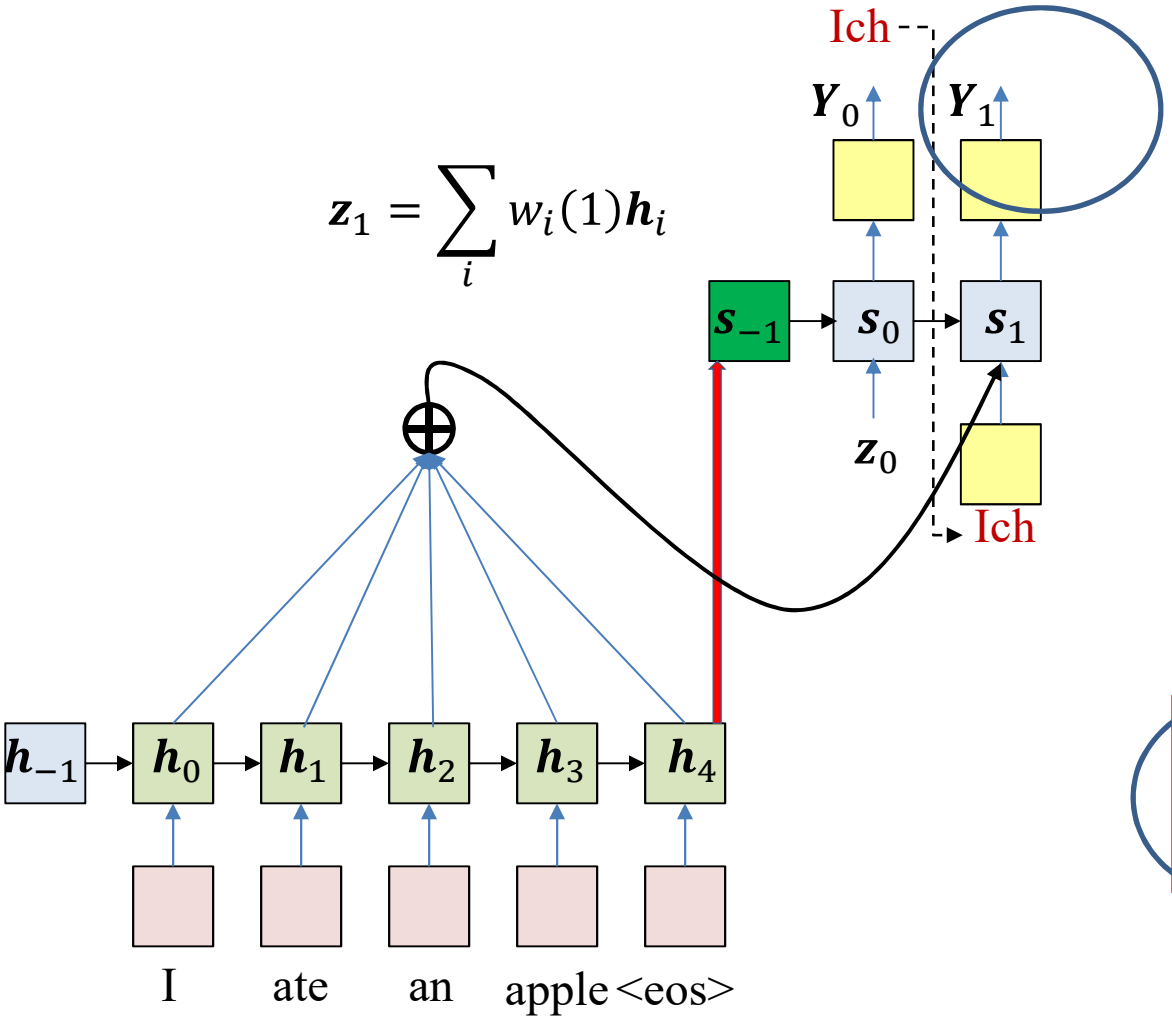
- **Terminate**
  - When the current most likely path overall ends in <eos>
    - Or continue producing more outputs (each of which terminates in <eos>) to get N-best outputs

Termination: <eos>



- **Terminate**
  - Paths cannot continue once the output an <eos>
    - So paths may be different lengths
      - Select the most likely sequence ending in <eos> across *all* terminating sequences

What does the attention learn?



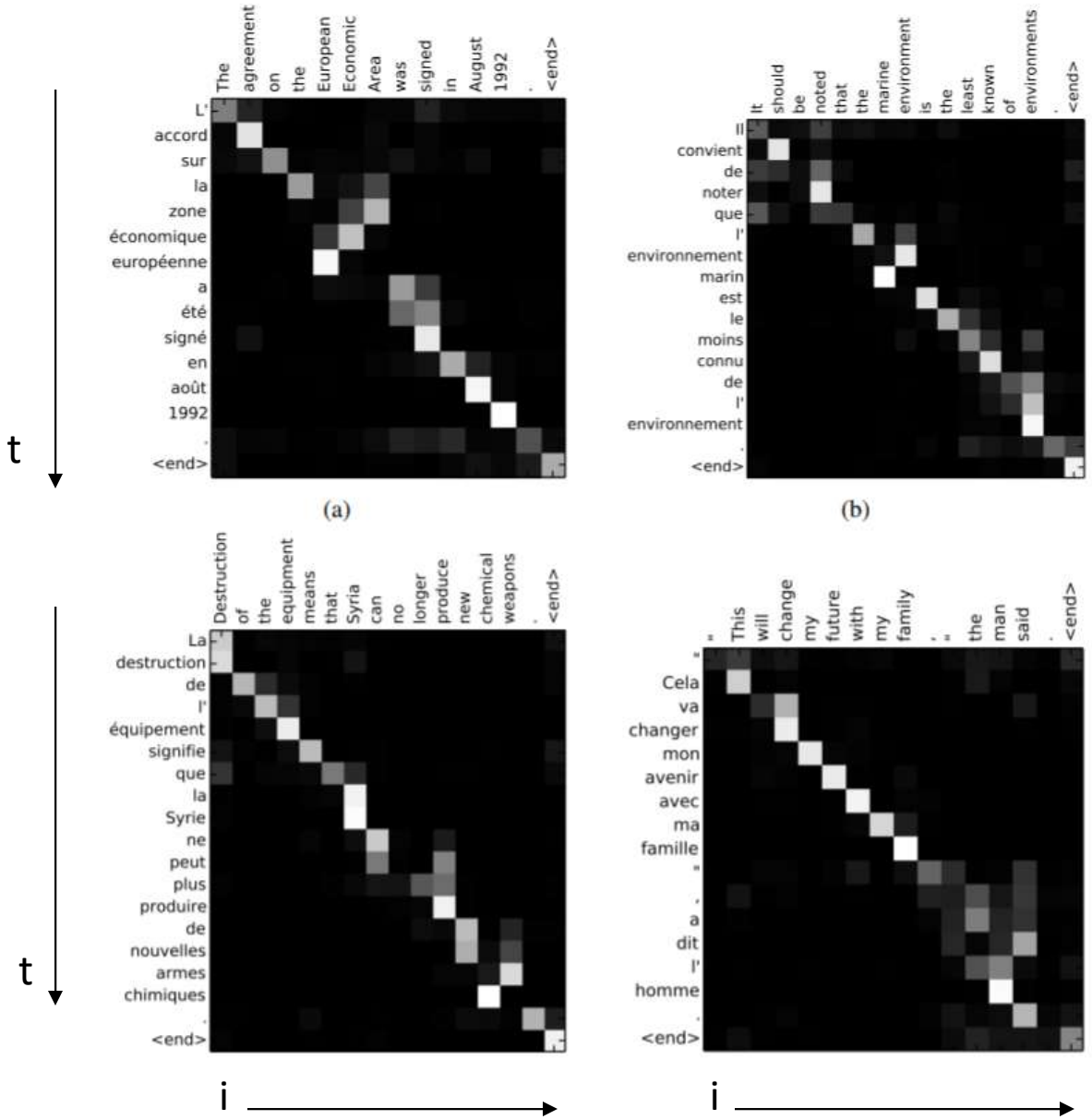
$$g(\boldsymbol{h}_i, \boldsymbol{s}_0) = \boldsymbol{h}_i^T \boldsymbol{W}_g \boldsymbol{s}_0$$

$$e_i(1) = g(\boldsymbol{h}_i, \boldsymbol{s}_0)$$

$$w_i(1) = \frac{\exp(e_i(1))}{\sum_j \exp(e_j(1))}$$

- The key component of this model is the attention weight
  - It captures the relative importance of each position in the input to the current output

“Alignments” example: Bahdanau et al.



Plot of $w_i(t)$
Color shows value (white is larger)

Note how most important input words for any output word get automatically highlighted

The general trend is somewhat linear because word order is roughly similar in both languages

Translation Examples

Source	An admitting privilege is the right of a doctor to admit a patient to a hospital or a medical centre to carry out a diagnosis or a procedure, based on his status as a health care worker at a hospital.
Reference	Le privilège d'admission est le droit d'un médecin, en vertu de son statut de membre soignant d'un hôpital, d'admettre un patient dans un hôpital ou un centre médical afin d'y délivrer un diagnostic ou un traitement.
RNNenc-50	Un privilège d'admission est le droit d'un médecin de reconnaître un patient à l'hôpital ou un centre médical d'un diagnostic ou de prendre un diagnostic en fonction de son état de santé.
RNNsearch-50	Un privilège d'admission est le droit d'un médecin d'admettre un patient à un hôpital ou un centre médical pour effectuer un diagnostic ou une procédure, selon son statut de travailleur des soins de santé à l'hôpital.
Google Translate	Un privilège admettre est le droit d'un médecin d'admettre un patient dans un hôpital ou un centre médical pour effectuer un diagnostic ou une procédure, fondée sur sa situation en tant que travailleur de soins de santé dans un hôpital.

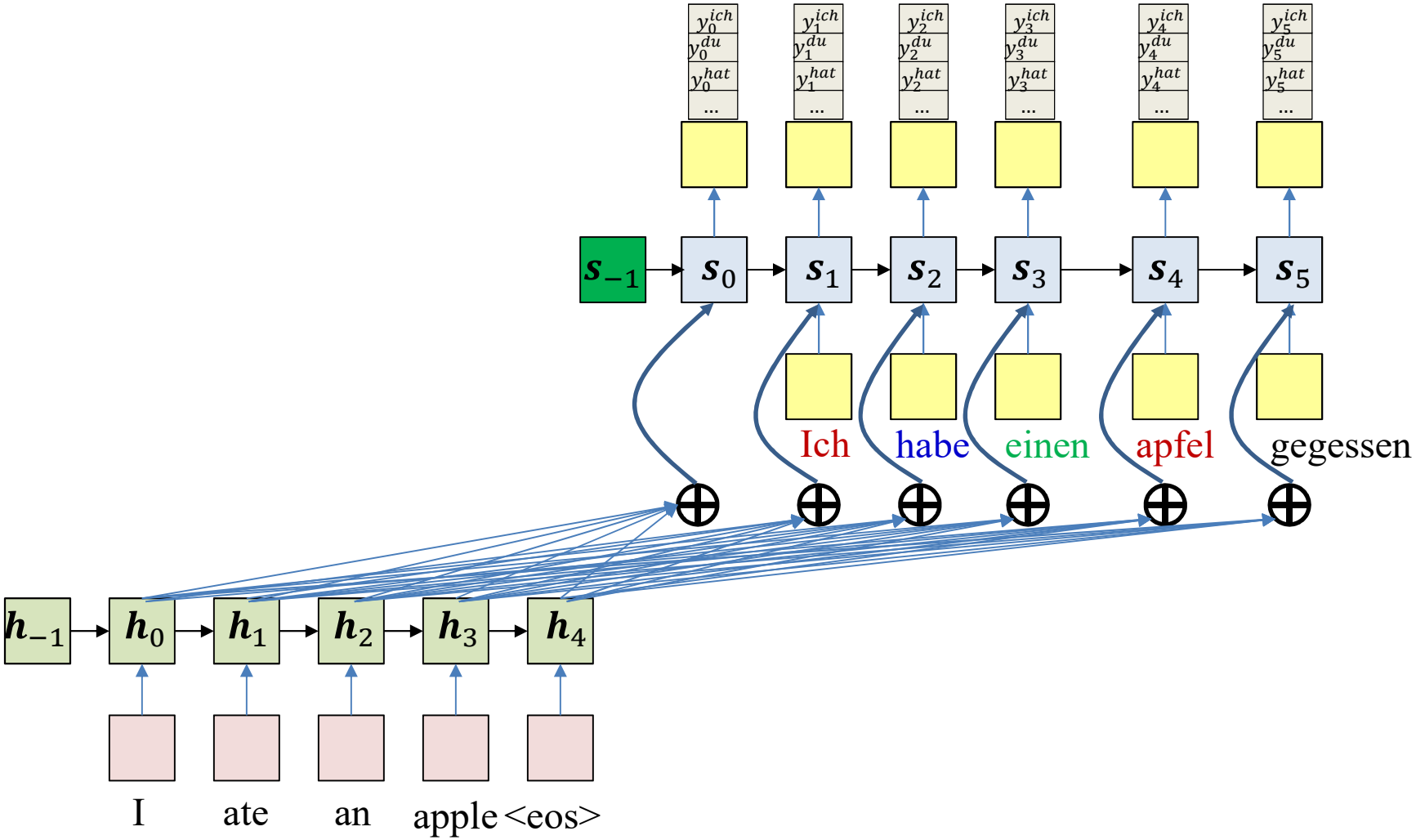
Source	This kind of experience is part of Disney's efforts to "extend the lifetime of its series and build new relationships with audiences via digital platforms that are becoming ever more important," he added.
Reference	Ce type d'expérience entre dans le cadre des efforts de Disney pour "étendre la durée de vie de ses séries et construire de nouvelles relations avec son public grâce à des plateformes numériques qui sont de plus en plus importantes", a-t-il ajouté.
RNNenc-50	Ce type d'expérience fait partie des initiatives du Disney pour "prolonger la durée de vie de ses nouvelles et de développer des liens avec les lecteurs numériques qui deviennent plus complexes.
RNNsearch-50	Ce genre d'expérience fait partie des efforts de Disney pour "prolonger la durée de vie de ses séries et créer de nouvelles relations avec des publics via des plateformes numériques de plus en plus importantes", a-t-il ajouté.
Google Translate	Ce genre d'expérience fait partie des efforts de Disney à "étendre la durée de vie de sa série et construire de nouvelles relations avec le public par le biais des plates-formes numériques qui deviennent de plus en plus important", at-il ajouté.

- Bahdanau et al. 2016

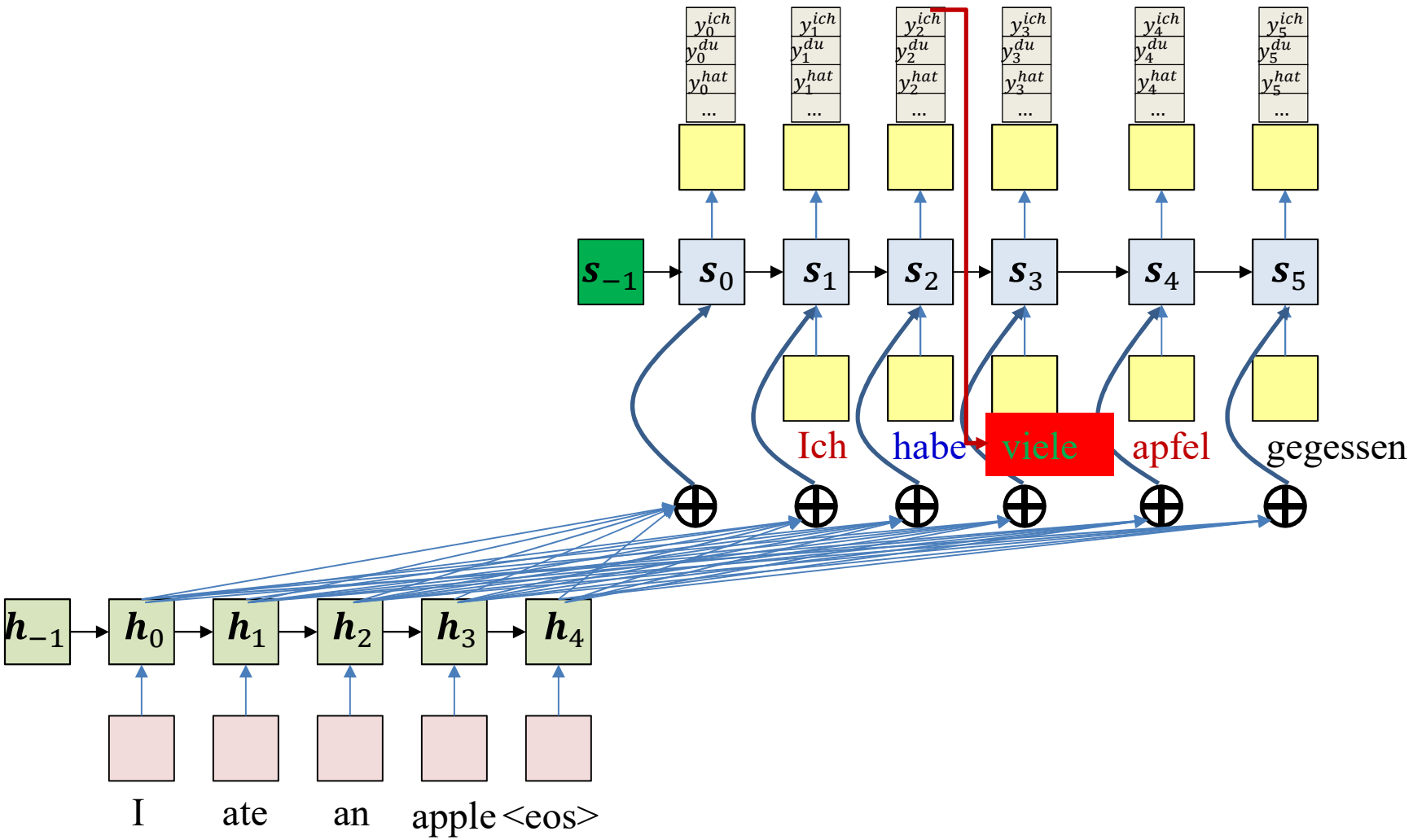
Training the network

- We have seen how a trained network can be used to compute outputs
  - Convert one sequence to another

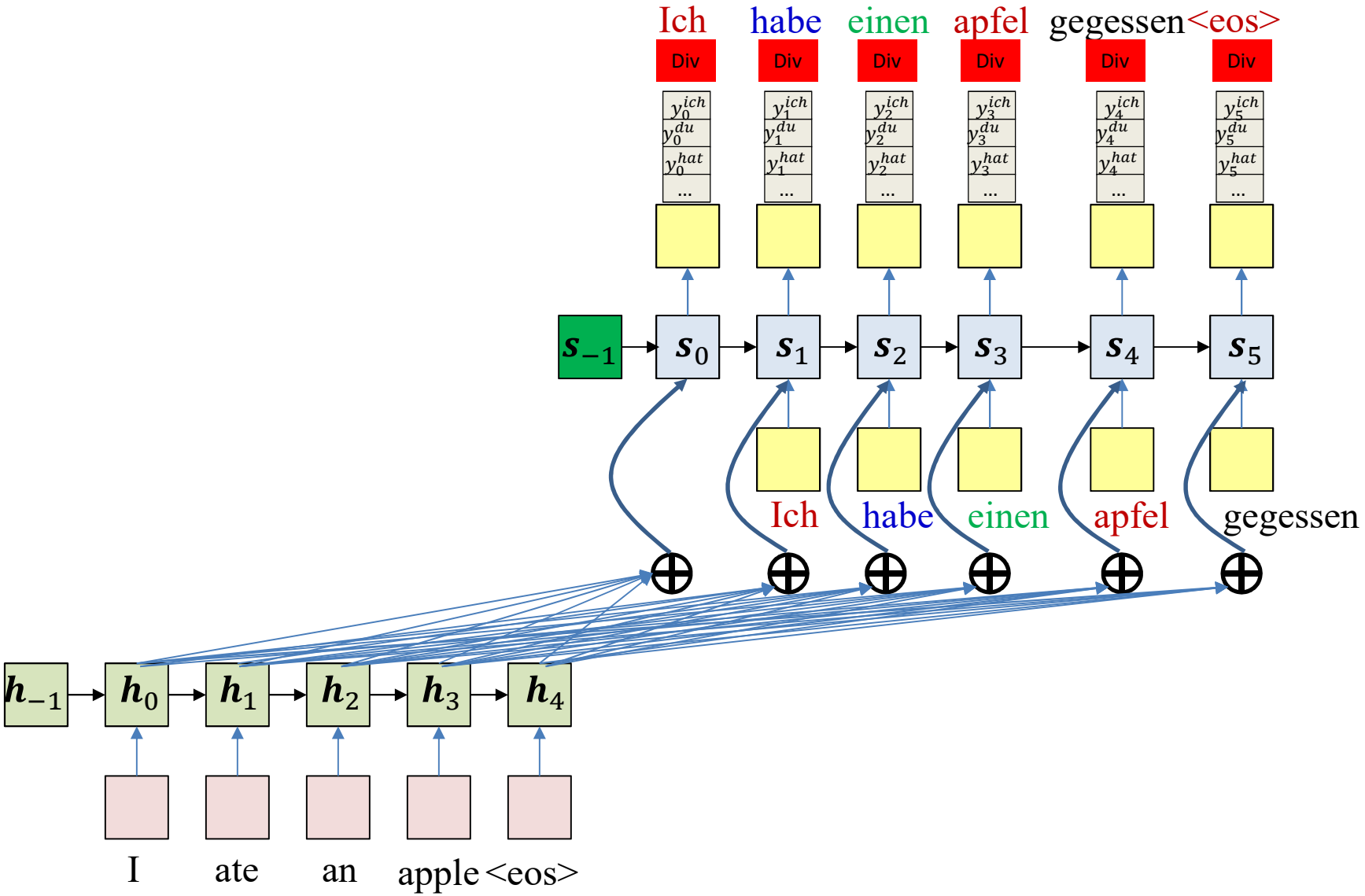
- Lets consider training..



- Given training input (source sequence, target sequence) pairs
- **Forward pass**: Pass the actual input sequence through the encoder
  - At each time the output is a probability distribution over words

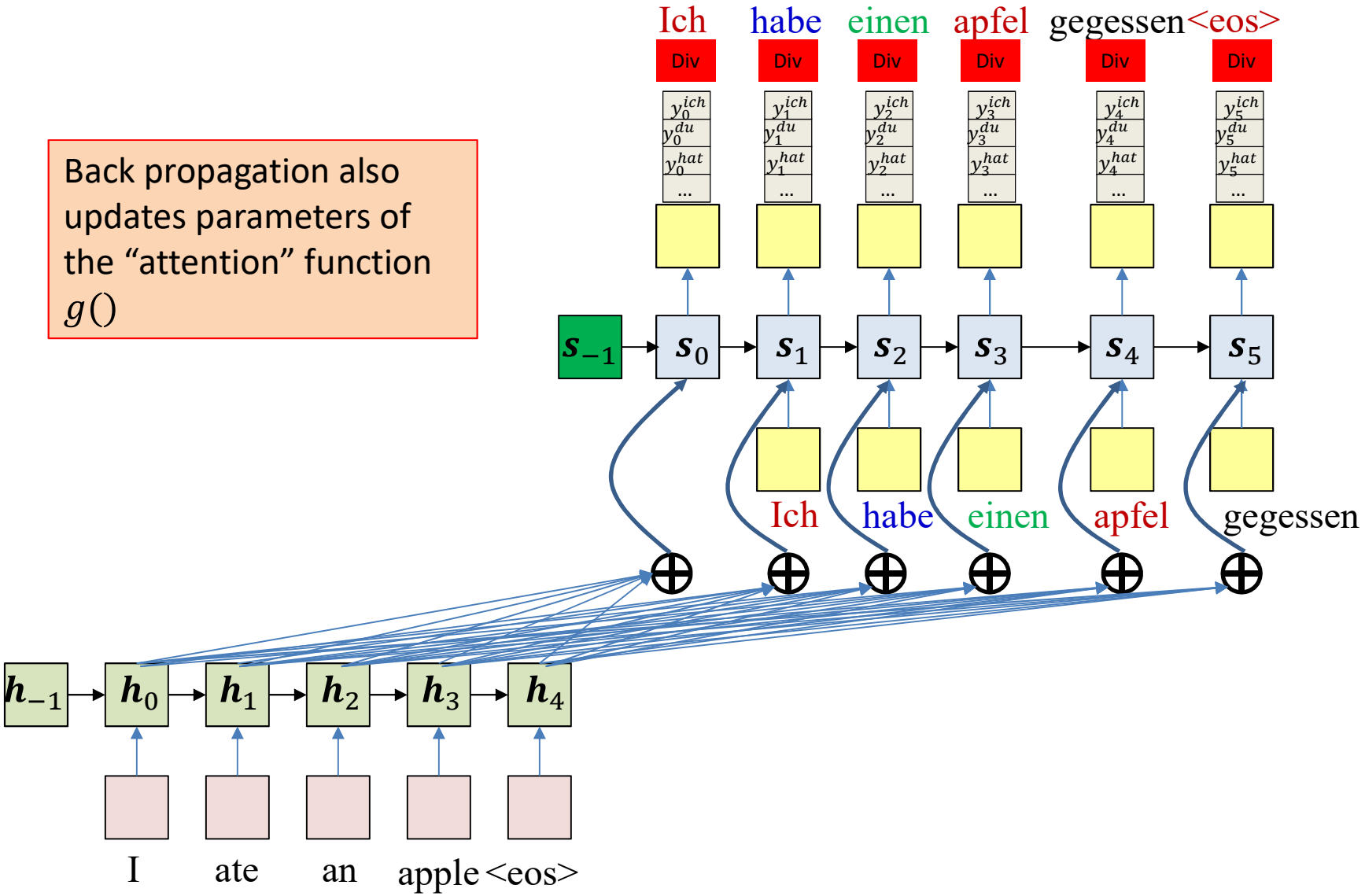


- Given training input (source sequence, target sequence) pairs
- **Forward pass**: Pass the actual input sequence through the encoder
  - At each time the output is a probability distribution over words
  - To make training more robust, occasionally pass *sampled (generated)* output word instead of actual word



- **Backward pass**: Compute a divergence between target output and output distributions
  - Backpropagate derivatives through the network

Back propagation also updates parameters of the "attention" function $g()$



- **Backward pass**: Compute a divergence between target output and output distributions
  - Backpropagate derivatives through the network

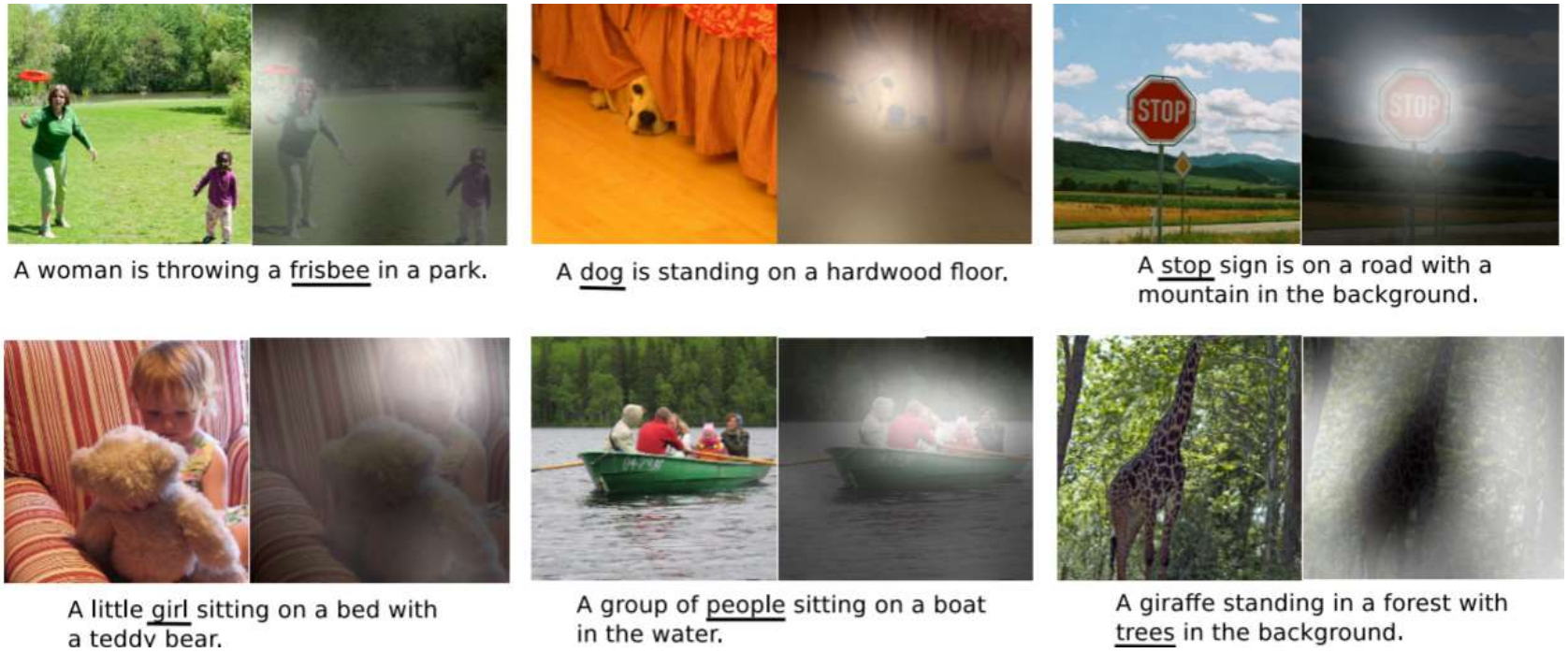
Various extensions

- Attention: Local attention vs global attention
  - E.g. “Effective Approaches to Attention-based Neural Machine Translation”, Luong et al., 2015
  - Other variants
- Bidirectional processing of input sequence
  - Bidirectional networks in encoder
  - E.g. “Neural Machine Translation by Jointly Learning to Align and Translate”, Bahdanau et al. 2016

Some impressive results..

- Attention-based models are currently responsible for the state of the art in many sequence-conversion systems
  - Machine translation
    - Input: Speech in source language
    - Output: Speech in target language
  - Speech recognition
    - Input: Speech audio feature vector sequence
    - Output: Transcribed word or character sequence

Attention models in image captioning



- "Show attend and tell: Neural image caption generation with visual attention", Xu et al., 2016
- Encoder network is a convolutional neural network
  - Filter outputs at each location are the equivalent of $\boldsymbol{h}_i$ in the regular sequence-to-sequence model

In closing

- Have looked at various forms of sequence-to-sequence models
- Generalizations of recurrent neural network formalisms
- For more details, please refer to papers
  - Post on piazza if you have questions
- Will appear in HW4: **Speech recognition with attention models**