Chapter ML:IX (continued)

IX. Deep Learning

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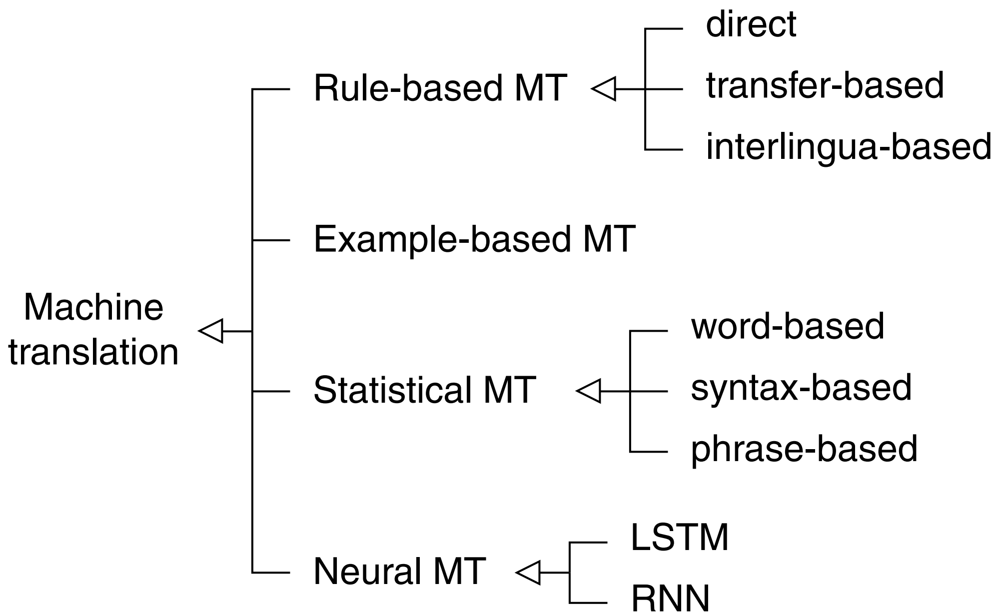
RNNs for Machine Translation

Statistical Machine Translation (SMT)



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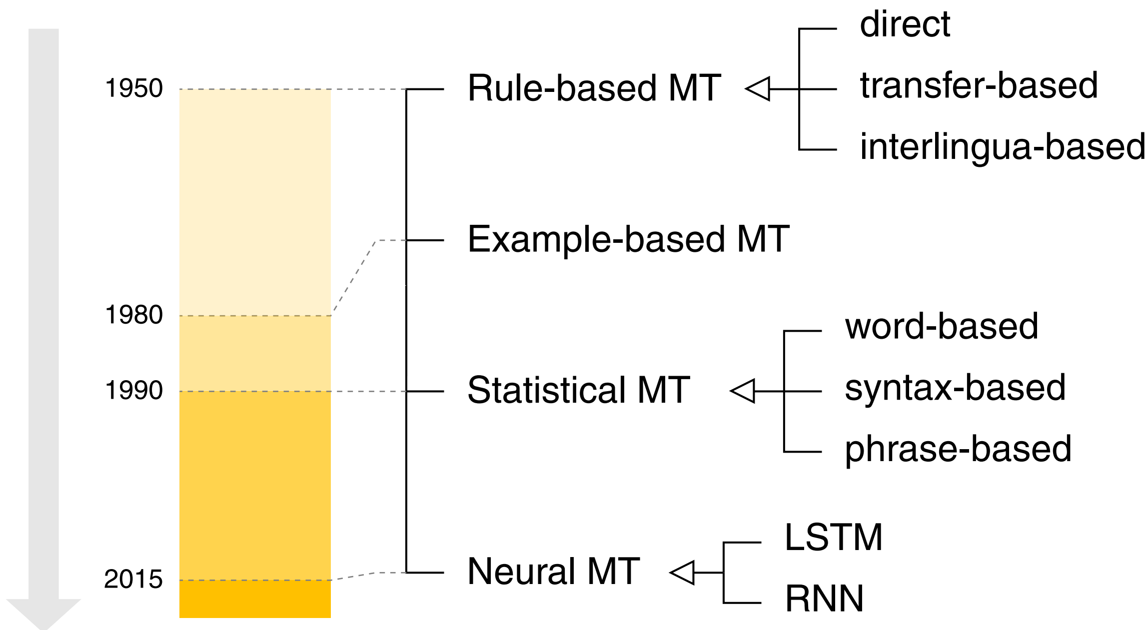
RNNs for Machine Translation

Statistical Machine Translation (SMT) (continued)



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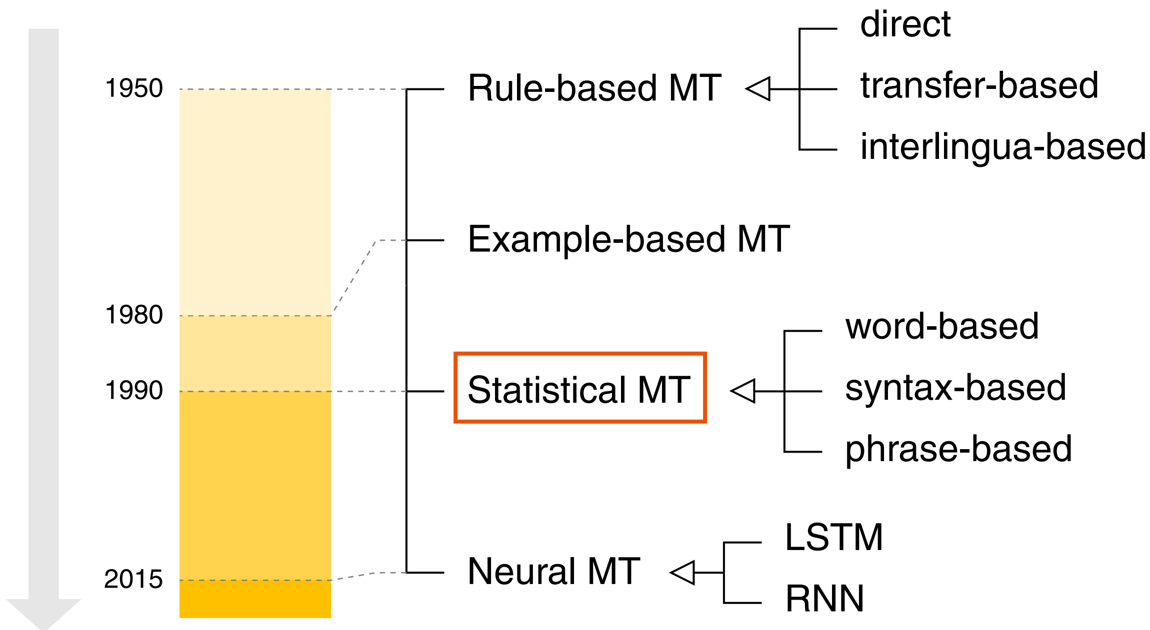
RNNs for Machine Translation

Statistical Machine Translation (SMT) (continued)



“Noisy channel” model applied to SMT:

Learn from a parallel corpus D a probabilistic model, $P(Y \mid X)$, which can be used to decode the channel input (the target sentence y, e.g. in German) from the channel output (the source sentence x in a foreign language (e.g., English)).

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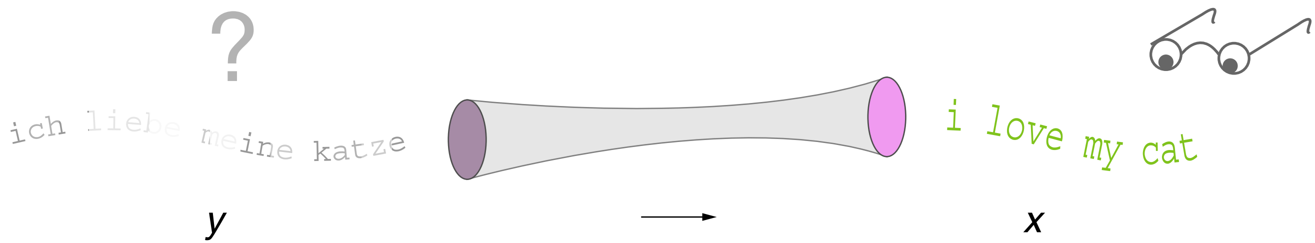
RNNs for Machine Translation

Statistical Machine Translation (SMT) (continued)



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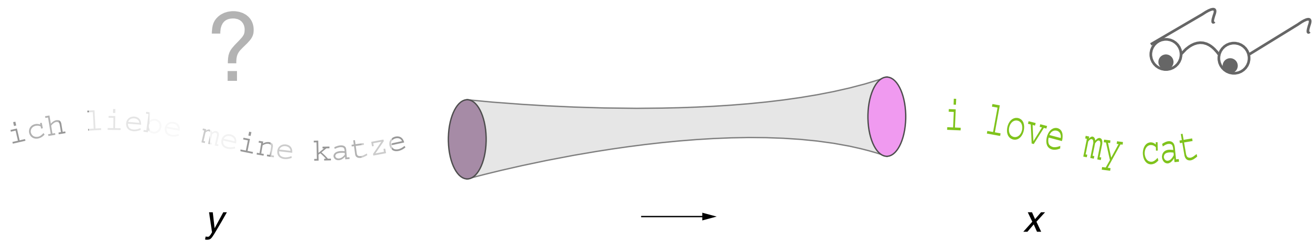
RNNs for Machine Translation

Statistical Machine Translation (SMT) (continued)



$$p\big(\text{“ich jage eine katze”} \mid \text{“i love my cat”}\big)$$
$$p\big(\text{“ich habe keine katze”} \mid \text{“i love my cat”}\big)$$
$$\vdots$$
$$p\big(\text{“ich liebe meine katze”} \mid \text{“i love my cat”}\big)$$

$$p\big(\text{German\_target\_sentence} \mid \text{English\_source\_sentence}\big)$$

$$p\big(\text{sentence\_in\_own\_language} \mid \text{sentence\_in\_foreign\_language}\big)$$

$$p(y \mid x)$$

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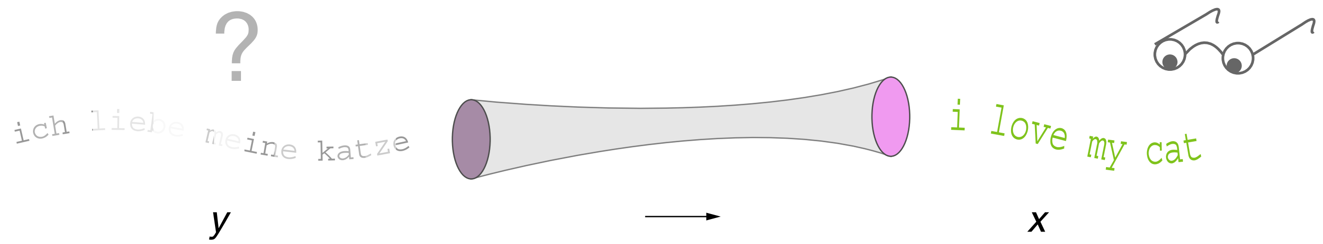
RNNs for Machine Translation

Statistical Machine Translation (SMT) (continued)



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$$p(\text{German\_target\_sentence} \mid \text{English\_source\_sentence})$$

$$p(\text{sentence\_in\_own\_language} \mid \text{sentence\_in\_foreign\_language})$$

$$p(y \mid x)$$

Task: Given a sentence x in a foreign language (here: English), what is the most probable translation y in our own language (here: German)?

$$p(y \mid x) \rightarrow \max$$

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Remarks:

- Noisy Channel model I. When the (German) sentence y was transmitted over a noisy channel, it got corrupted and came out as sentence x in a foreign language (English). The task is to recover the original sentence, i.e., to decode (= translate) the English (source) into German (target).

- Noisy Channel model II. We can observe only x, and we ask ourselves which sentence y might have induced x. Among the candidates for y we search the most probable sentence, which we then consider as translation of x. I.e., the Noisy Channel model does *not* take sentence y and looks for a translation x (= varies x), but takes "the condition" x as given and varies among the y.

  Tackling this translation task with coupled RNNs (= Neural Machine Translation) reflects this view: Conditioned by the hidden vector encoding of x, denoted as $\mathbf{y}^{\text{e}}(T^{\text{e}})$ in the figure, the decoder has to generate the most probable sentence y.

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RNNs for Machine Translation

Statistical Machine Translation (SMT) (continued)

Based on a parallel corpus D, the best translation y of a sentence x given in the foreign language maximizes under D the probability $p(y \mid x)$:

$$\text{argmax}_y\, p(y \mid x) = \text{argmax}_y\; p(x \mid y) \cdot p(y) \qquad \Leftarrow$$

$$P(Y \mid X) = \frac{P(X \mid Y) \cdot P(Y)}{P(X)}$$

$X \,\widehat{=}\,$ X$=x$, $\quad x \,\widehat{=}\,$ English sentence

$Y \,\widehat{=}\,$ Y$=y$, $\quad y \,\widehat{=}\,$ German sentence

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RNNs for Machine Translation

Statistical Machine Translation (SMT) (continued)

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$$\text{argmax}_y\, p(y \mid x) = \text{argmax}_y\; p(x \mid y) \cdot \boxed{p(y)} \qquad \Leftarrow$$

$$P(Y \mid X) = \frac{P(X \mid Y) \cdot P(Y)}{P(X)}$$

$X \mathrel{\widehat{=}}$ X$=x$, $\quad x \mathrel{\widehat{=}}$ English sentence

$Y \mathrel{\widehat{=}}$ Y$=y$, $\quad y \mathrel{\widehat{=}}$ German sentence

1. $p(y)$ is called “language model” and takes care of the *fluency* in the target language. It is modeled as $p(y_1, \ldots, y_m) = \prod_{i=1}^{m} p(y_i \mid y_{i-(n-1)}, \ldots, y_{i-1})$. Training data are (monolingual) corpora in the target language.

2. $p(x \mid y)$ is called “translation model” and captures the translation *fidelity* between two languages. It is modeled as $p(x, \mathbf{a} \mid y)$, where “$\mathbf{a}$” is a vector of alignment features. Training data are bilingual corpora.

3. argmax$_y$ is called “decoder” and operationalizes the *search* for the maximization problem. Keyword: beam search

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RNNs for Machine Translation

Statistical Machine Translation (SMT) (continued)

Based on a parallel corpus D, the best translation y of a sentence x given in the foreign language maximizes under D the probability $p(y \mid x)$:

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RNNs for Machine Translation

Statistical Machine Translation (SMT) (continued)

Based on a parallel corpus D, the best translation y of a sentence x given in the foreign language maximizes under D the probability $p(y \mid x)$:

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3. argmax_y is called "decoder" and operationalizes the *search* for the maximization problem. Keyword: beam search

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Remarks (statistical machine translation) :

- Although $p(y \mid x)$ can be maximized directly, Bayes rule is applied since the decomposition of $p(y \mid x)$ into $p(x \mid y)$ and $p(y)$ comes along with a number of advantages.

- In the language model syntax, $p(y) = p(y_1, y_2, \ldots, y_m)$ denotes the probability of the event to observe the sentence $y = y_1 y_2 \ldots y_m$, where y_1 corresponds to the first word of the sentence, y_2 to the second, etc. The y_i are realizations of random variables, which can be written in any order as arguments of $p()$. I.e., to capture the word order, y_i does not only denote the word, but also its position: y_i corresponds to the event "Word y_i at position i."

  In summary, $p(y_1, y_2, \ldots, y_m)$ is a short form of $P(\mathsf{Y}_1 = y_1, \mathsf{Y}_2 = y_2, \ldots, \mathsf{Y}_m = y_m)$, where the Y_i are random variables whose realizations are the possible words at position i. Note that these random variables are neither independent nor identically distributed.

- Learning $p(x, \mathbf{a} \mid y)$ from a parallel corpus D is a highly sophisticated endeavor since the alignments features are complex and given as latent variables only.

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RNNs for Machine Translation

Neural Machine Translation (NMT)

Concept:

- Machine translation with a multilayer perceptron (MLP).
- Network architecture is a sequence-to-sequence model:

  1. Encoder RNN, calculates an encoding of the source sentence x.
  2. Decoder RNN, generates the target sentence y. The decoder RNN is a *conditional* language model—it is conditioned on the RNN encoding.

- Optimization (loss minimization) is done for the network as a whole, which means that backpropagation is performed "end-to-end".

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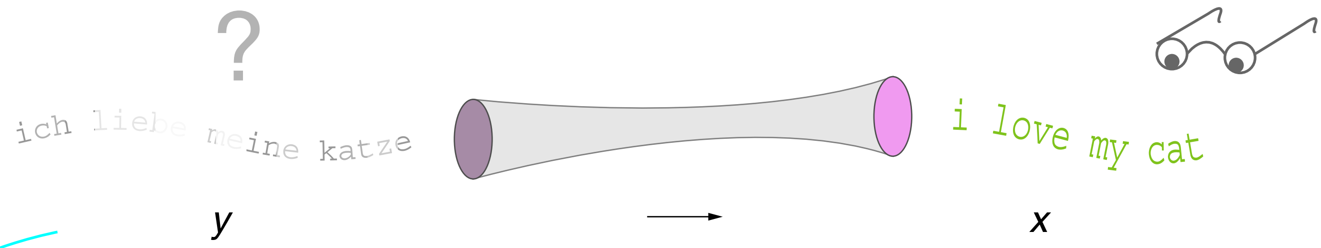
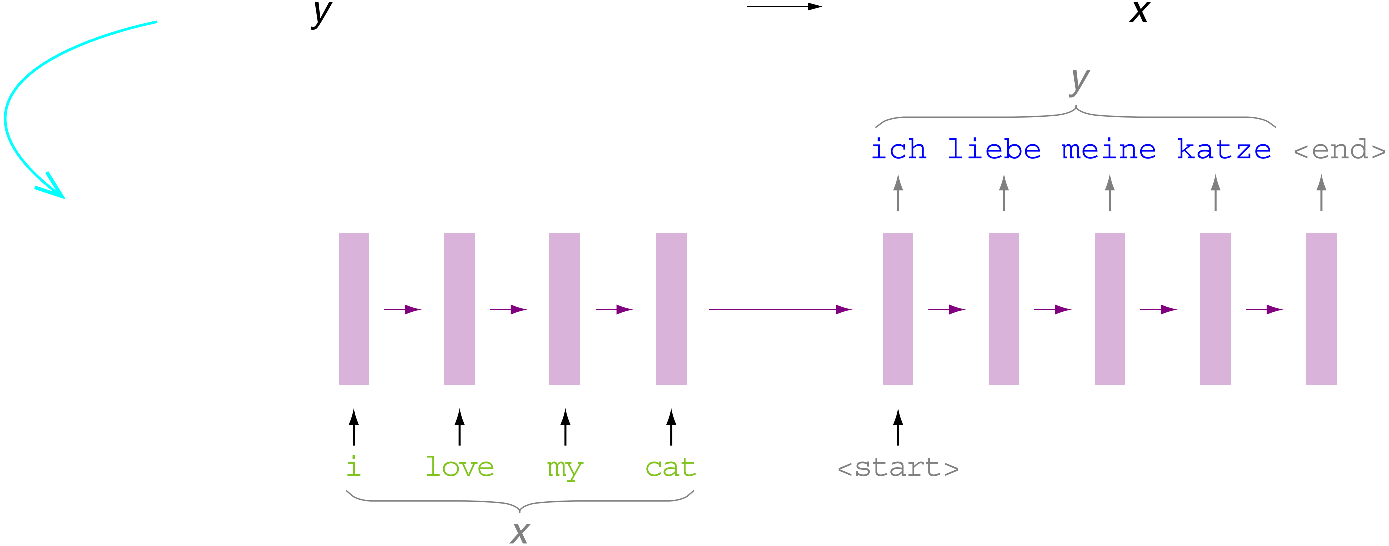
RNNs for Machine Translation

Neural Machine Translation (NMT) (continued)

Concept:





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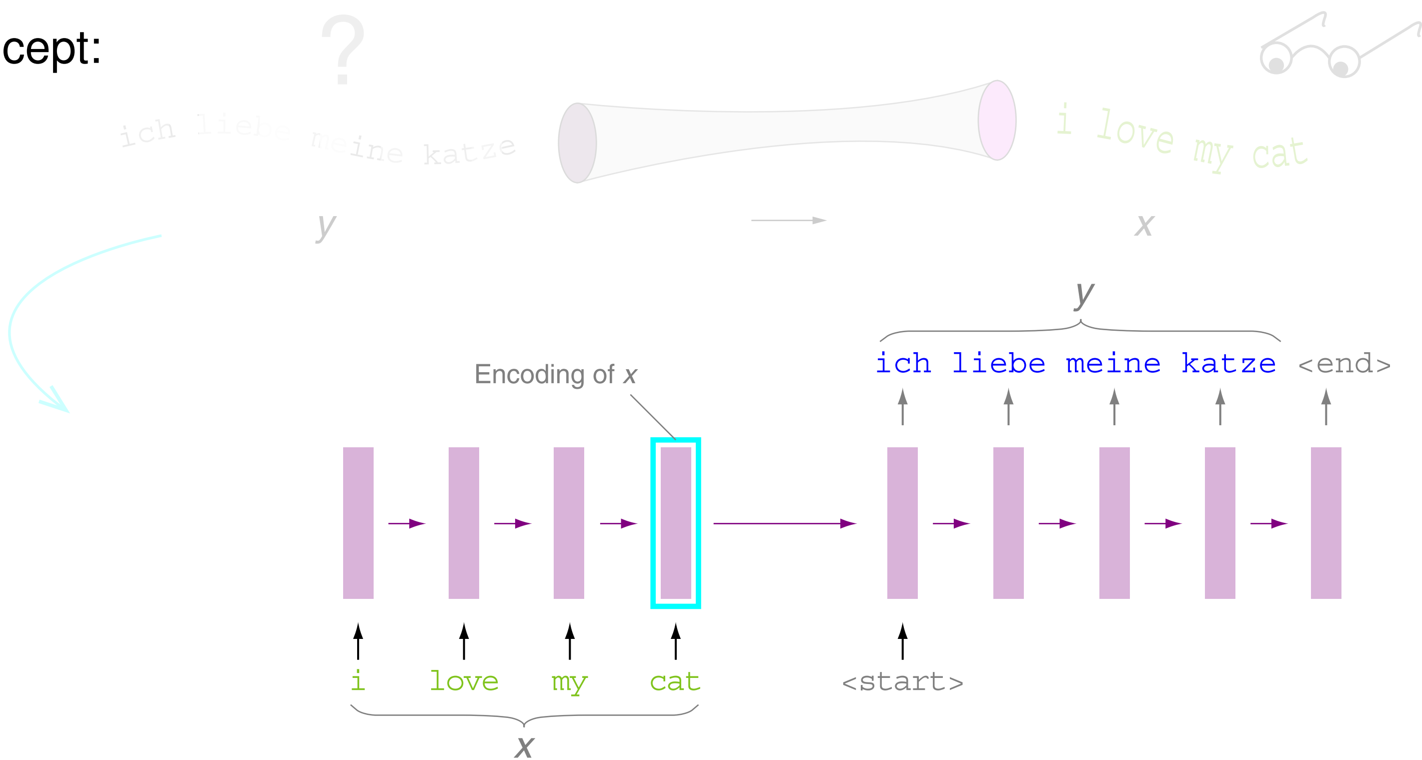
RNNs for Machine Translation

Neural Machine Translation (NMT) (continued)

Concept:



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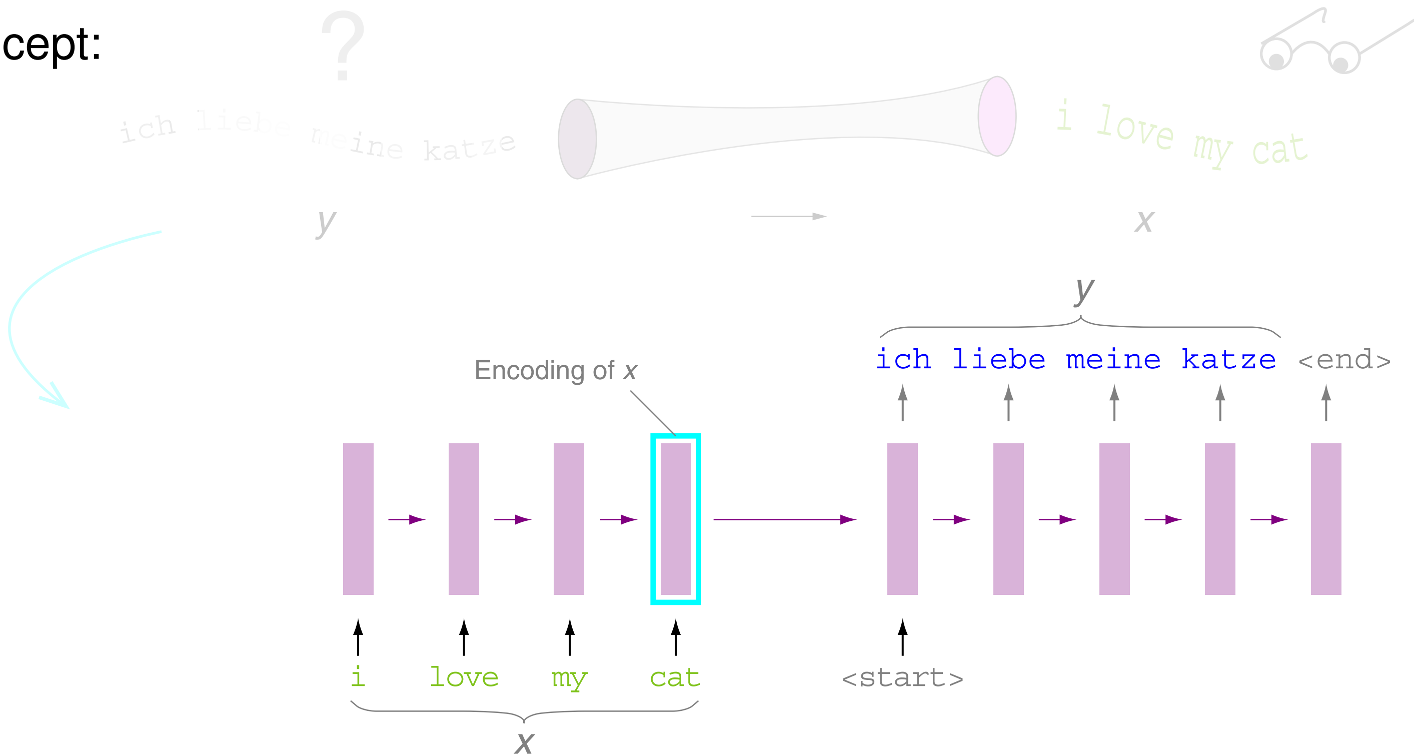
Neural Machine Translation (NMT) (continued)

Concept:



The sequence-to-sequence RNN directly calculates $p(y \mid x)$:

$$p(y \mid x) \;=\; p(y_1 \mid x) \cdot p(y_2 \mid y_1, x) \cdot p(y_3 \mid y_1, y_2, x) \cdot \ldots \cdot p(y_\tau \mid y_1, \ldots, y_{\tau-1}, x)$$

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Remarks:

- "End-to-end" is not an architectural feature of a network (observe that every network is used in this way). It is a strategy for solving a task by *not* decomposing it, but by processing the original input-output examples in an indivisible manner.

- The sequence-to-sequence model is an example of a conditional language model: (1) It is a language model because the decoder is predicting the next word y_t of the target sentence based on the preceding words $y_1, \ldots, y_{t-1}$. (2) It is conditional because its predictions are also conditioned on the source sentence x. [Manning 2021, lecture CS224N]

- In the following slides, the hidden vector $\mathbf{y}^{\text{e}}(T^{\text{e}})$ represents the RNN encoding of the source sentence x. In particular,

  - the words x_t from a source (input) sentence x are denoted as $\mathbf{x}(t)$,
  - the words y_t from a output sentence are denoted as $\mathbf{y}(t)$,
  - the words y_t from a target sentence y are denoted as $\mathbf{c}(t)$.

  Note that we have not distinguished whether y_t is output or target.

- Don't get confused: The input y of the noisy channel becomes the target (output) of the RNN. Similary, the output x of the noisy channel becomes the source (input) of the RNN.

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RNNs for Machine Translation

Types of Learning Tasks [Recap]

(S1) sequence $\rightarrow$ class

sentence $\rightarrow \{\oplus, \ominus\}$

`i love my cat` $\rightarrow \oplus$

(S2) class $\rightarrow$ sequence

$\{\oplus, \ominus\} \rightarrow$ sentence

$\oplus \rightarrow$ `i love my cat`

(S3) sequence $\rightarrow$ sequence

English sentence $\rightarrow$ German sentence

`i love my cat` $\rightarrow$ `ich liebe meine katze`

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RNNs for Machine Translation

(S3) Sequence-to-Sequence: Machine Translation

- I love my cat. $\rightarrow$ Ich liebe meine Katze.
- Cats and dogs lap water. $\rightarrow$ Katzen und Hunde lecken Wasser.
- It is raining cats and dogs. $\rightarrow$ Es regnet in Strömen.
- Cats and dogs are not allowed. $\rightarrow$ Katzen oder Hunde sind nicht erlaubt.

Vocabulary^e : (`allowed and are cat cats dogs i is it lap love my not raining water`)

Vocabulary^d : (`erlaubt es hunde ich in katze lecken liebe meine nicht regnet sind strömen und wasser <start> <end>`)

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RNNs for Machine Translation

(S3) Sequence-to-Sequence: Machine Translation (continued)

- I love my cat. $\rightarrow$ Ich liebe meine Katze.
- Cats and dogs lap water. $\rightarrow$ Katzen und Hunde lecken Wasser.
- It is raining cats and dogs. $\rightarrow$ Es regnet in Strömen.
- Cats and dogs are not allowed. $\rightarrow$ Katzen oder Hunde sind nicht erlaubt.

Vocabulary^{e} : (`allowed and are cat cats dogs i is it lap love my not raining water`)

Vocabulary^{d} : (`erlaubt es hunde ich in katze lecken liebe meine nicht regnet sind strömen und wasser <start> <end>`)

Input: $$[\,[\,[\,[\,[\mathbf{x},\ \mathbf{y}(0)\,],\ \mathbf{y}(1)],\ \mathbf{y}(2)],\ldots],\ \mathbf{y}(\tau{-}1)],\ \ \mathbf{x} = \left[\begin{pmatrix}0\\ \vdots\\ 1\\ 0\\ \vdots\end{pmatrix}, \begin{pmatrix}0\\ \vdots\\ \vdots\\ 1\\ 0\\ \vdots\end{pmatrix}, \begin{pmatrix}0\\ \vdots\\ \vdots\\ \vdots\\ 1\\ 0\\ \vdots\end{pmatrix}, \begin{pmatrix}0\\ \vdots\\ 1\\ 0\\ \vdots\\ \vdots\end{pmatrix}\right] \mathrel{\widehat{=}} \text{I love my cat}$$

Output: $$[\mathbf{y}(1), \mathbf{y}(2), \mathbf{y}(3), \ldots, \mathbf{y}(\tau^{\mathsf{d}})], \quad \mathbf{y}(0) \equiv \mathbf{c}(0) \mathrel{\widehat{=}} \texttt{<start>}, \quad \mathbf{y}(\tau) \mathrel{\widehat{=}} \mathbf{c}(5) \mathrel{\widehat{=}} \texttt{<end>}$$

RNNs for Machine Translation

(S3) Sequence-to-Sequence: Machine Translation (continued)

- I love my cat. $\rightarrow$ Ich liebe meine Katze.
- Cats and dogs lap water. $\rightarrow$ Katzen und Hunde lecken Wasser.
- It is raining cats and dogs. $\rightarrow$ Es regnet in Strömen.
- Cats and dogs are not allowed. $\rightarrow$ Katzen oder Hunde sind nicht erlaubt.

Vocabulary^{e} : (`allowed and are cat cats dogs i is it lap love my not raining water`)

Vocabulary^{d} : (`erlaubt es hunde ich in katze lecken liebe meine nicht regnet sind strömen und wasser <start> <end>`)

Input: $[\,[\,[\,[\,[\mathbf{x},\ \mathbf{y}(0)],\ \mathbf{y}(1)],\ \mathbf{y}(2)],\ldots],\ \mathbf{y}(\tau{-}1)],\ \mathbf{x} = \left[\begin{pmatrix}0\\ \vdots\\ 1\\ 0\\ \vdots\end{pmatrix}, \begin{pmatrix}0\\ \vdots\\ 1\\ 0\\ \vdots\end{pmatrix}, \begin{pmatrix}0\\ \vdots\\ 1\\ 0\\ \vdots\end{pmatrix}, \begin{pmatrix}0\\ 1\\ 0\\ \vdots\end{pmatrix}\right]$ $\widehat{=}$ I love my cat

Output: $[\mathbf{y}(1), \mathbf{y}(2), \mathbf{y}(3), \ldots, \mathbf{y}(\tau^{\mathrm{d}})]$, $\quad \mathbf{y}(0) \equiv \mathbf{c}(0) \mathrel{\widehat{=}}$ `<start>`, $\quad \mathbf{y}(\tau) \mathrel{\widehat{=}} \mathbf{c}(5) \mathrel{\widehat{=}}$ `<end>`

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RNNs for Machine Translation

(S3) Sequence-to-Sequence: Machine Translation (continued)

- I love my cat. → Ich liebe meine Katze.
- Cats and dogs lap water. → Katzen und Hunde lecken Wasser.
- It is raining cats and dogs. → Es regnet in Strömen.
- Cats and dogs are not allowed. → Katzen oder Hunde sind nicht erlaubt.

Vocabulary$^{\text{e}}$: (`allowed and are cat cats dogs i is it lap love my not raining water`)

Vocabulary$^{\text{d}}$: (`erlaubt es hunde ich in katze lecken liebe meine nicht regnet sind strömen und wasser <start> <end>`)

Input: $[\,[\,[\,[\,[\mathbf{x},\ \mathbf{y}(0)],\ \mathbf{y}(1)],\ \mathbf{y}(2)],\ldots],\ \mathbf{y}(\tau{-}1)],\ \mathbf{x} = \left[\begin{pmatrix}0\\ \vdots\\ 1\\ 0\\ \vdots\end{pmatrix},\begin{pmatrix}0\\ \vdots\\ 1\\ 0\\ \vdots\end{pmatrix},\begin{pmatrix}0\\ \vdots\\ 1\\ 0\\ \vdots\end{pmatrix},\begin{pmatrix}0\\ 1\\ 0\\ \vdots\end{pmatrix}\right] \mathrel{\widehat{=}}$ I love my cat

Output: $[\mathbf{y}(1), \mathbf{y}(2), \mathbf{y}(3), \ldots, \mathbf{y}(\tau^{\text{d}})], \quad \mathbf{y}(0) \equiv \mathbf{c}(0) \mathrel{\widehat{=}} \texttt{<start>}, \quad \mathbf{y}(\tau) \mathrel{\widehat{=}} \mathbf{c}(5) \mathrel{\widehat{=}} \texttt{<end>}$

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RNNs for Machine Translation

(S3) Sequence-to-Sequence: Machine Translation (continued)

- I love my cat. $\rightarrow$ Ich liebe meine Katze.
- Cats and dogs lap water. $\rightarrow$ Katzen und Hunde lecken Wasser.
- It is raining cats and dogs. $\rightarrow$ Es regnet in Strömen.
- Cats and dogs are not allowed. $\rightarrow$ Katzen oder Hunde sind nicht erlaubt.

Vocabulary$^{\mathrm{e}}$: (`allowed and are cat cats dogs i is it lap love my not raining water`)

Vocabulary$^{\mathrm{d}}$: (`erlaubt es hunde ich in katze lecken liebe meine nicht regnet sind strömen und wasser` `<start>` `<end>`)

Input: $[\,[\,[\,[\,[\mathbf{x},\ \mathbf{y}(0)],\ \mathbf{y}(1)],\ \mathbf{y}(2)],\ldots],\ \mathbf{y}(\tau-1)],\ \ \mathbf{x} = \left[\begin{pmatrix}0\\ \vdots\\ 1\\ 0\\ \vdots\end{pmatrix}, \begin{pmatrix}0\\ \vdots\\ 1\\ 0\\ \vdots\end{pmatrix}, \begin{pmatrix}0\\ \vdots\\ 1\\ 0\end{pmatrix}, \begin{pmatrix}0\\ \vdots\\ 1\\ 0\\ \vdots\end{pmatrix}\right]$ $\mathrel{\widehat{=}}$ I love my cat

Output: $[\mathbf{y}(1), \mathbf{y}(2), \mathbf{y}(3), \ldots, \mathbf{y}(\tau^{\mathrm{d}})]$, $\quad \mathbf{y}(0) \equiv \mathbf{c}(0) \mathrel{\widehat{=}}$ `<start>`, $\quad \mathbf{y}(\tau) \mathrel{\widehat{=}} \mathbf{c}(5) \mathrel{\widehat{=}}$ `<end>`

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- I love my cat. $\rightarrow$ Ich liebe meine Katze.
- Cats and dogs lap water. $\rightarrow$ Katzen und Hunde lecken Wasser.
- It is raining cats and dogs. $\rightarrow$ Es regnet in Strömen.
- Cats and dogs are not allowed. $\rightarrow$ Katzen oder Hunde sind nicht erlaubt.

Vocabulary^{e} : (`allowed and are cat cats dogs i is it lap love my not raining water`)

Vocabulary^{d} : (`erlaubt es hunde ich in katze lecken liebe meine nicht regnet sind strömen und wasser <start> <end>`)

Input: $[\,[\,[\,[\,[\mathbf{x},\ \mathbf{y}(0)],\ \mathbf{y}(1)],\ \mathbf{y}(2)],\ldots],\ \mathbf{y}(\tau{-}1)],\quad \mathbf{x} = \left[\begin{pmatrix}0\\ \vdots\\ 1\\ 0\\ \vdots\end{pmatrix}, \begin{pmatrix}0\\ \vdots\\ 1\\ 0\\ \vdots\end{pmatrix}, \begin{pmatrix}0\\ \vdots\\ 1\\ 0\\ \vdots\end{pmatrix}, \begin{pmatrix}0\\ 1\\ 0\\ \vdots\end{pmatrix}\right]$ $\widehat{=}$ I love my cat

Output: $[\mathbf{y}(1), \mathbf{y}(2), \mathbf{y}(3), \ldots, \mathbf{y}(\tau^{\mathrm{d}})],\quad \mathbf{y}(0) \equiv \mathbf{c}(0)\ \widehat{=}$ `<start>`, $\quad \mathbf{y}(\tau)\ \widehat{=}\ \mathbf{c}(5)\ \widehat{=}$ `<end>`

RNNs for Machine Translation

(S3) Sequence-to-Sequence: Machine Translation (continued)

- I love my cat. → Ich liebe meine Katze.
- Cats and dogs lap water. → Katzen und Hunde lecken Wasser.
- It is raining cats and dogs. → Es regnet in Strömen.
- Cats and dogs are not allowed. → Katzen oder Hunde sind nicht erlaubt.

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Vocabulary$^{\text{d}}$: (`erlaubt es hunde ich in katze lecken liebe meine nicht regnet sind strömen und wasser` <start> <end>)

Input: $[\,[\,[\,[\,[\mathbf{x},\ \mathbf{y}(0)],\ \mathbf{y}(1)],\ \mathbf{y}(2)], \ldots],\ \mathbf{y}(\tau-1)],\quad \mathbf{x} = \left[\begin{pmatrix}0\\ \vdots\\ 1\\ 0\\ \vdots\end{pmatrix}, \begin{pmatrix}0\\ \vdots\\ 1\\ 0\\ \vdots\end{pmatrix}, \begin{pmatrix}0\\ \vdots\\ 1\\ 0\\ \vdots\end{pmatrix}, \begin{pmatrix}0\\ 1\\ 0\\ \vdots\end{pmatrix}\right] \;\widehat{=}$ I love my cat

Output: $[\mathbf{y}(1), \mathbf{y}(2), \mathbf{y}(3), \ldots, \mathbf{y}(\tau^{\text{d}})],\quad \mathbf{y}(0) \equiv \mathbf{c}(0) \;\widehat{=}$ <start>, $\quad \mathbf{y}(\tau) \;\widehat{=}\; \mathbf{c}(5) \;\widehat{=}$ <end>

Target: $[\mathbf{c}(1), \ldots, \mathbf{c}(5)] = \left[\begin{pmatrix}0\\ \vdots\\ 1\\ 0\\ \vdots\end{pmatrix}, \begin{pmatrix}0\\ \vdots\\ 1\\ 0\\ \vdots\end{pmatrix}, \begin{pmatrix}0\\ \vdots\\ 1\\ 0\\ \vdots\end{pmatrix}, \begin{pmatrix}0\\ \vdots\\ 1\\ 0\\ \vdots\end{pmatrix}, \begin{pmatrix}0\\ \vdots\\ \vdots\\ \vdots\\ 1\end{pmatrix}\right] \;\widehat{=}$ Ich liebe meine Katze

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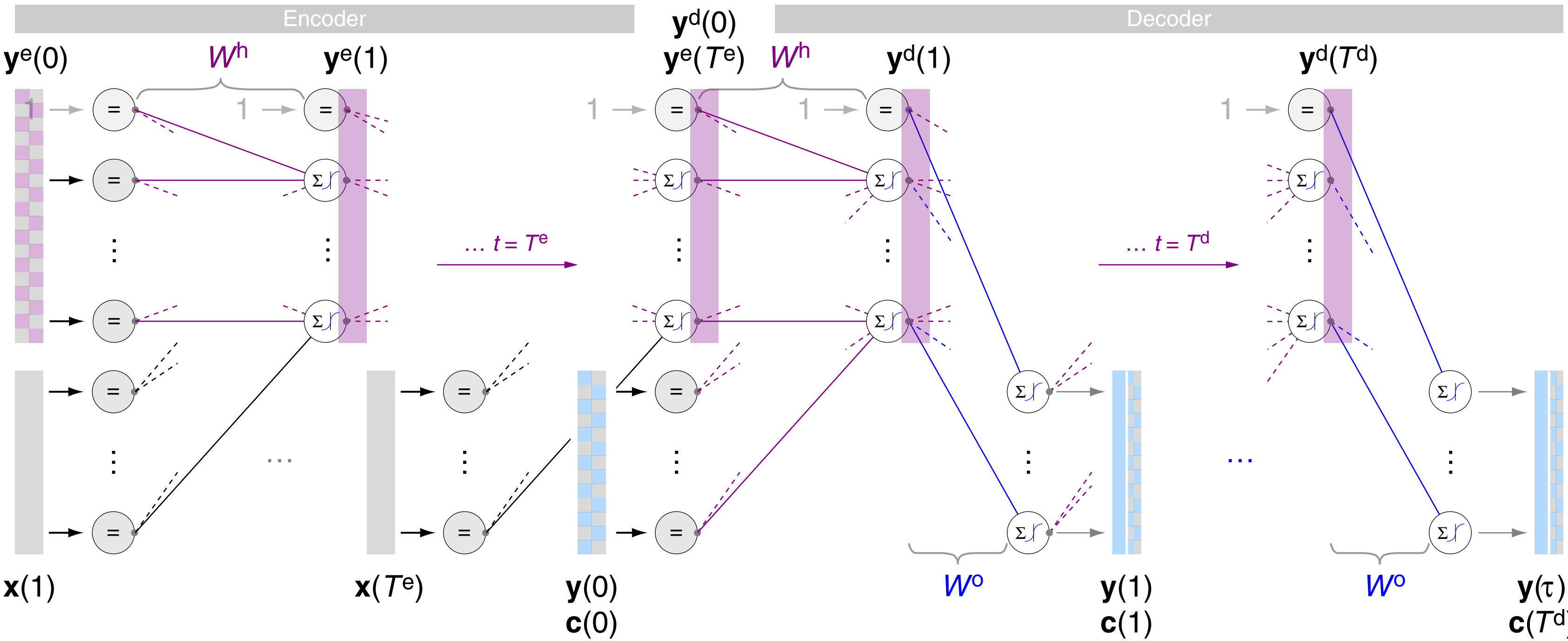
RNNs for Machine Translation

(S3) Sequence-to-Sequence Mapping with RNNs



Input:

$\mathbf{x},\ [\mathbf{y}(1), \dots, \mathbf{y}(\tau{-}1)]$

Hidden:

$$\mathbf{y}^{\mathrm{e}}(t) = \boldsymbol{\sigma}\left(W^{\mathrm{h}}\begin{pmatrix}\mathbf{y}^{\mathrm{e}}(t{-}1)\\ \mathbf{x}(t)\end{pmatrix}\right),\ t = 1, \dots, T^{\mathrm{e}}$$

$$\mathbf{y}^{\mathrm{d}}(t) = \boldsymbol{\sigma}\left(W^{\mathrm{h}}\begin{pmatrix}\mathbf{y}^{\mathrm{d}}(t{-}1)\\ \mathbf{y}(t{-}1)\end{pmatrix}\right),\ t = 1, \dots, \tau$$

Target:

$[\mathbf{c}(1), \dots, \mathbf{c}(T)]$

$\mathbf{c}(T) \mathrel{\widehat{=}}$ <end>

Output:

$$\mathbf{y}(t) = \boldsymbol{\sigma}_1\left(W^{\mathrm{o}}\,\mathbf{y}^{\mathrm{d}}(t)\right),\ t = 1, \dots, \tau$$

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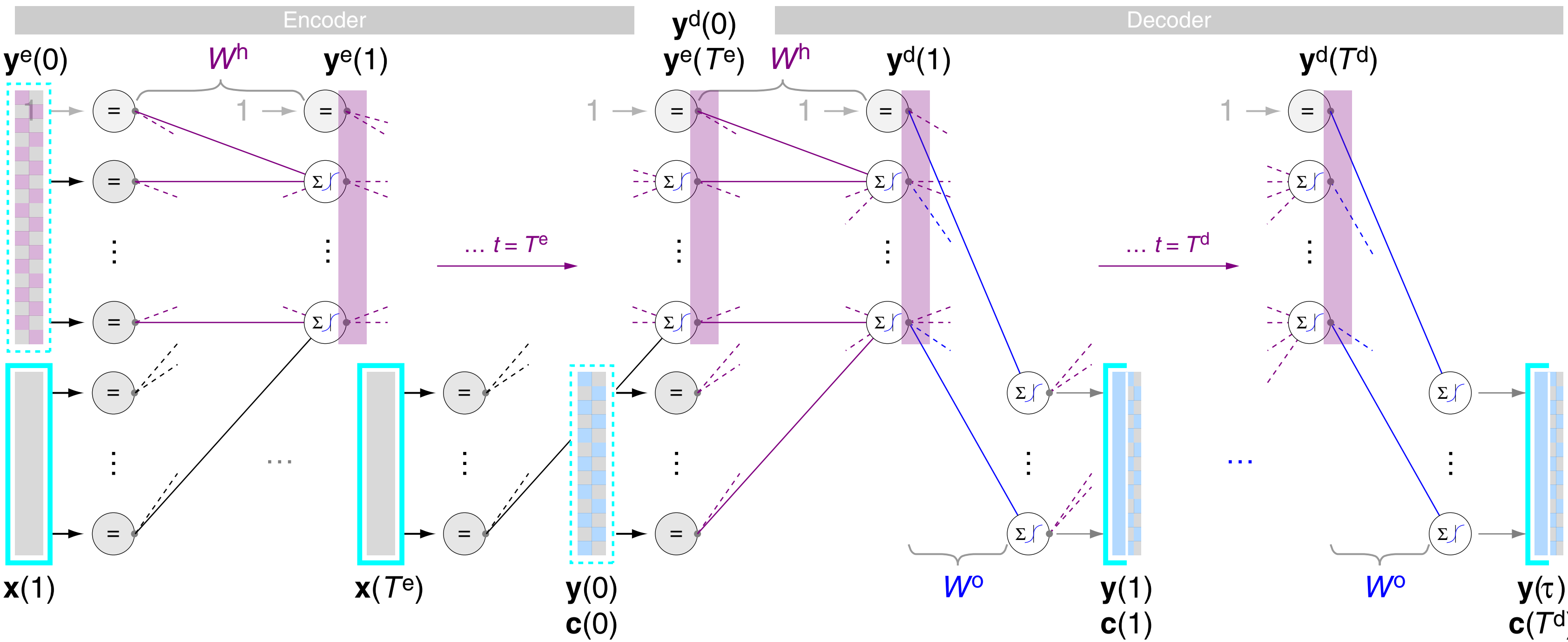
RNNs for Machine Translation

(S3) Sequence-to-Sequence Mapping with RNNs (continued)



Input:

$\mathbf{x}$, $[\mathbf{y}(1), \ldots, \mathbf{y}(\tau-1)]$

Output:

$\mathbf{y}(t) = \boldsymbol{\sigma}_1\left(W^{\text{o}}\,\mathbf{y}^{\text{d}}(t)\right), t = 1, \ldots, \tau$

Hidden:

$$\mathbf{y}^{\text{e}}(t) = \boldsymbol{\sigma}\left(W^{\text{h}}\begin{pmatrix}\mathbf{y}^{\text{e}}(t-1)\\ \mathbf{x}(t)\end{pmatrix}\right), t = 1, \ldots, T^{\text{e}}$$

$$\mathbf{y}^{\text{d}}(t) = \boldsymbol{\sigma}\left(W^{\text{h}}\begin{pmatrix}\mathbf{y}^{\text{d}}(t-1)\\ \mathbf{y}(t-1)\end{pmatrix}\right), t = 1, \ldots, \tau$$

Target:

$[\mathbf{c}(1), \ldots, \mathbf{c}(T)]$

$\mathbf{c}(T) \mathrel{\widehat{=}}$ <end>

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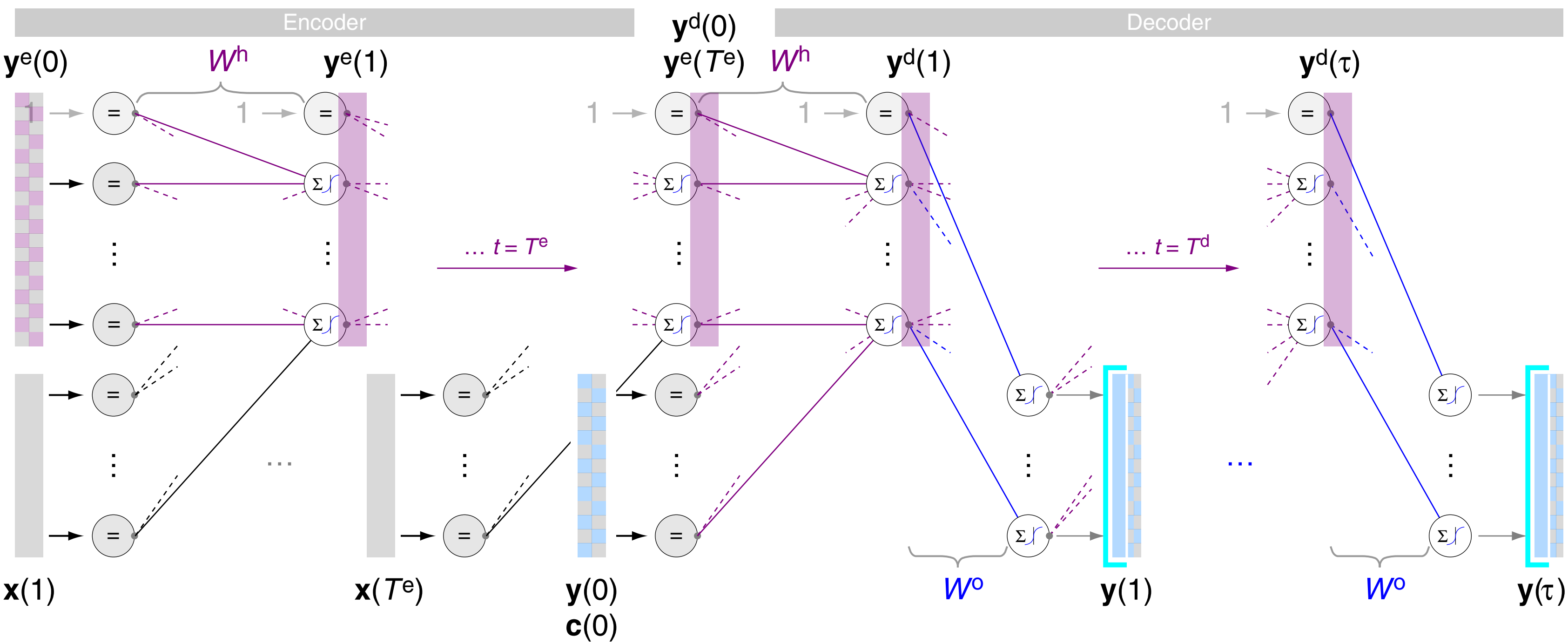
RNNs for Machine Translation

(S3) Sequence-to-Sequence Mapping with RNNs (continued)



Input:

$\mathbf{x}$, $[\mathbf{y}(1), \ldots, \mathbf{y}(\tau-1)]$

Output:

$$\mathbf{y}(t) = \boldsymbol{\sigma}_1 \left(W^o \, \mathbf{y}^d(t) \right), t = 1, \ldots, \tau$$

Hidden:

$$\mathbf{y}^e(t) = \boldsymbol{\sigma} \left(W^h \begin{pmatrix} \mathbf{y}^e(t-1) \\ \mathbf{x}(t) \end{pmatrix} \right), t = 1, \ldots, T^e$$

$$\mathbf{y}^d(t) = \boldsymbol{\sigma} \left(W^h \begin{pmatrix} \mathbf{y}^d(t-1) \\ \mathbf{y}(t-1) \end{pmatrix} \right), t = 1, \ldots, \tau$$

Target:

$[\mathbf{c}(1), \ldots, \mathbf{c}(T)]$

$\mathbf{c}(T) \mathrel{\widehat{=}}$ <end>

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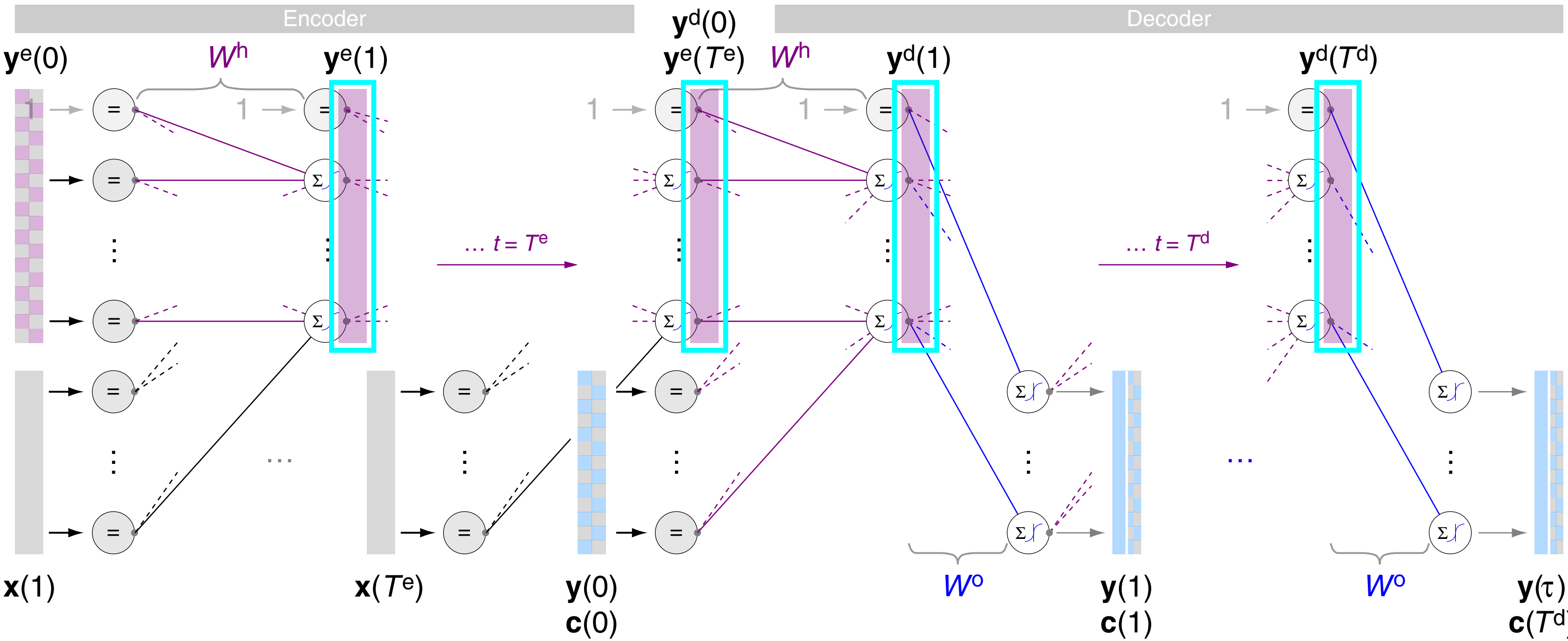
RNNs for Machine Translation

(S3) Sequence-to-Sequence Mapping with RNNs (continued)



Input:

$\mathbf{x}$, $[\mathbf{y}(1), \ldots, \mathbf{y}(\tau{-}1)]$

Output:

$$\mathbf{y}(t) = \boldsymbol{\sigma}_1\left(W^{o}\,\mathbf{y}^{d}(t)\right), t = 1, \ldots, \tau$$

Hidden:

$$\mathbf{y}^{e}(t) = \boldsymbol{\sigma}\left(W^{h}\begin{pmatrix}\mathbf{y}^{e}(t{-}1)\\ \mathbf{x}(t)\end{pmatrix}\right), t = 1, \ldots, T^{e}$$

$$\mathbf{y}^{d}(t) = \boldsymbol{\sigma}\left(W^{h}\begin{pmatrix}\mathbf{y}^{d}(t{-}1)\\ \mathbf{c}(t{-}1)\end{pmatrix}\right), t = 1, \ldots, T^{d}$$

Target:

$[\mathbf{c}(1), \ldots, \mathbf{c}(T)]$

$\mathbf{c}(T) \mathrel{\widehat{=}}$ <end>

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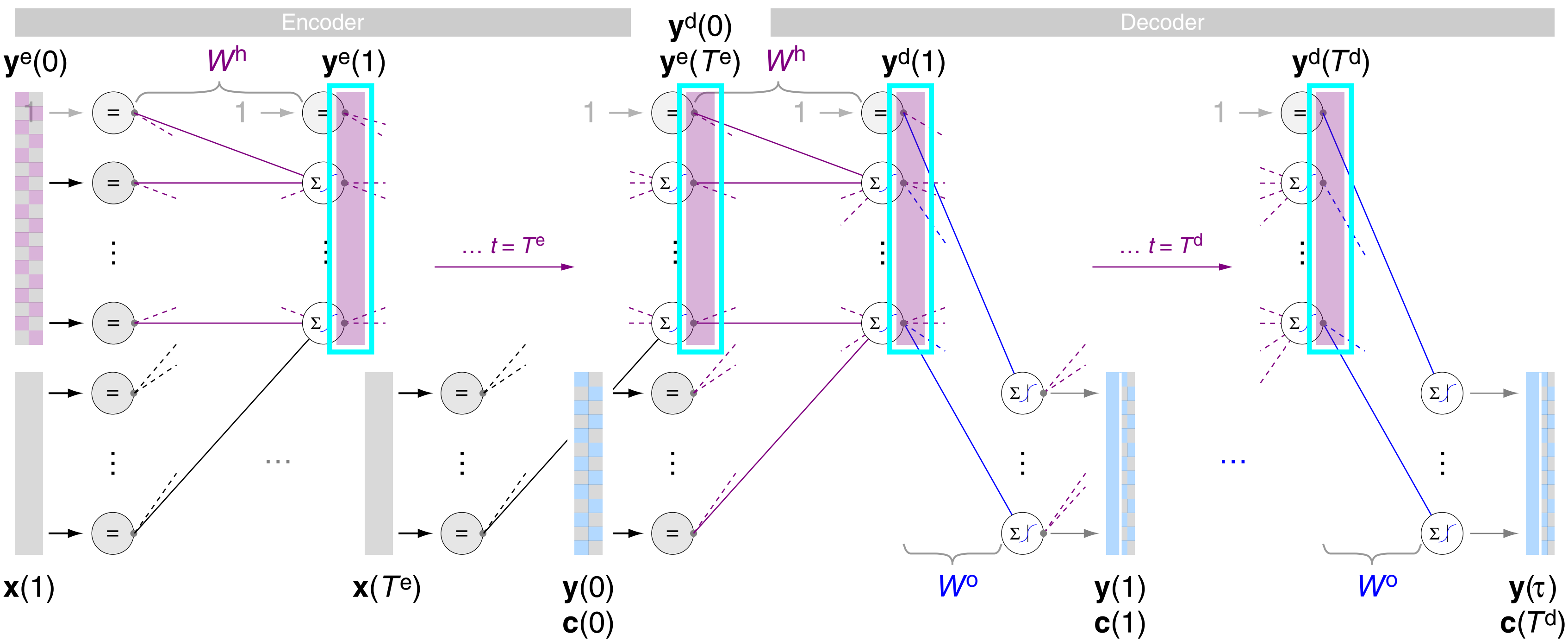
RNNs for Machine Translation

(S3) Sequence-to-Sequence Mapping with RNNs (continued)



Input:

$\mathbf{x},\ [\mathbf{y}(1), \ldots, \mathbf{y}(\tau-1)]$

Output:

$\mathbf{y}(t) = \boldsymbol{\sigma}_1 \left(W^{\mathrm{o}}\, \mathbf{y}^{\mathrm{d}}(t)\right), t = 1, \ldots, \tau$

Hidden:

$$\mathbf{y}^{\mathrm{e}}(t) = \boldsymbol{\sigma}\left(W^{\mathrm{h}}\begin{pmatrix}\mathbf{y}^{\mathrm{e}}(t-1)\\ \mathbf{x}(t)\end{pmatrix}\right), t = 1, \ldots, T^{\mathrm{e}}$$

$$\mathbf{y}^{\mathrm{d}}(t) = \boldsymbol{\sigma}\left(W^{\mathrm{h}}\begin{pmatrix}\mathbf{y}^{\mathrm{d}}(t-1)\\ \mathbf{y}(t-1)\end{pmatrix}\right), t = 1, \ldots, \tau$$

Target:

$[\mathbf{c}(1), \ldots, \mathbf{c}(T)]$

$\mathbf{c}(T) \mathrel{\widehat{=}} \text{<end>}$

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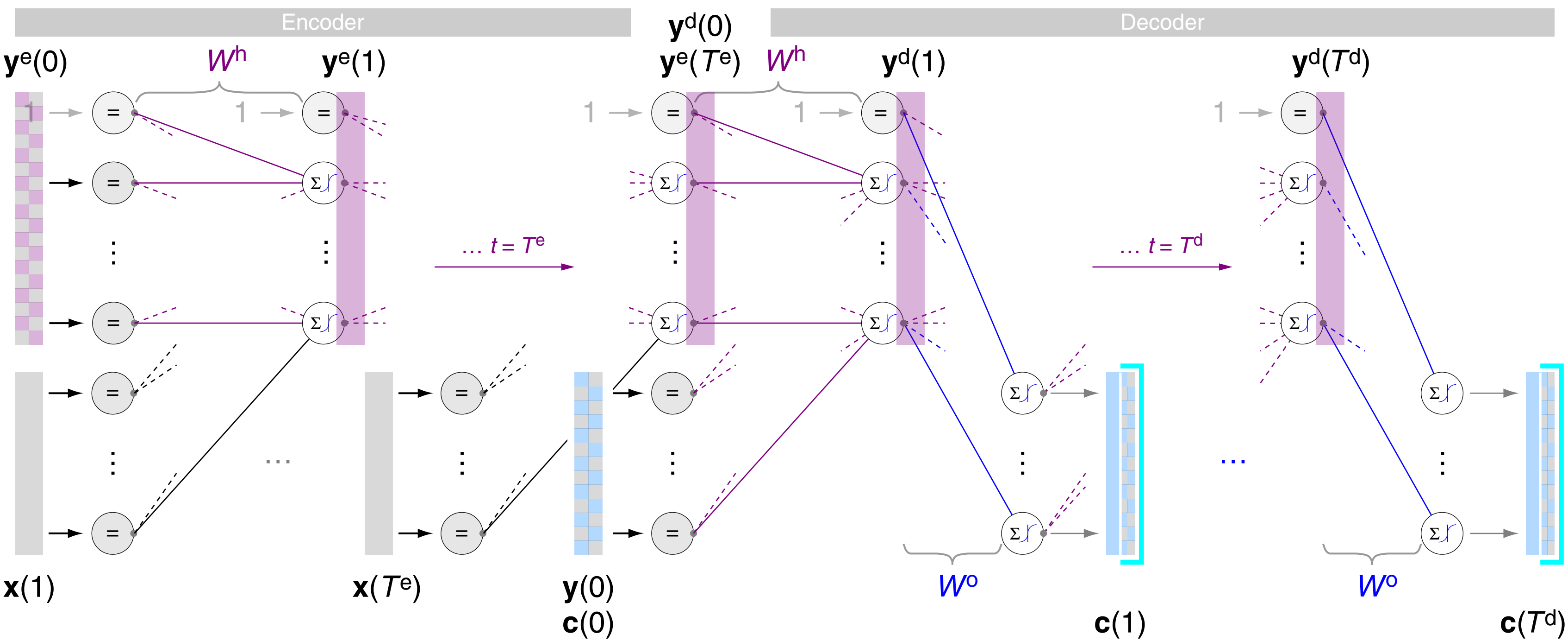
RNNs for Machine Translation

(S3) Sequence-to-Sequence Mapping with RNNs (continued)



Input:

$\mathbf{x}$, $[\mathbf{y}(1), \ldots, \mathbf{y}(\tau{-}1)]$

Output:

$$\mathbf{y}(t) = \boldsymbol{\sigma}_1 \left(W^{\mathrm{o}} \, \mathbf{y}^{\mathrm{d}}(t) \right), t = 1, \ldots, \tau$$

Hidden:

$$\mathbf{y}^{\mathrm{e}}(t) = \boldsymbol{\sigma} \left(W^{\mathrm{h}} \begin{pmatrix} \mathbf{y}^{\mathrm{e}}(t{-}1) \\ \mathbf{x}(t) \end{pmatrix} \right), t = 1, \ldots, T^{\mathrm{e}}$$

$$\mathbf{y}^{\mathrm{d}}(t) = \boldsymbol{\sigma} \left(W^{\mathrm{h}} \begin{pmatrix} \mathbf{y}^{\mathrm{d}}(t{-}1) \\ \mathbf{y}(t{-}1) \end{pmatrix} \right), t = 1, \ldots, \tau$$

Target:

$[\mathbf{c}(1), \ldots, \mathbf{c}(T)]$

$\mathbf{c}(T) \mathrel{\widehat{=}}$ <end>

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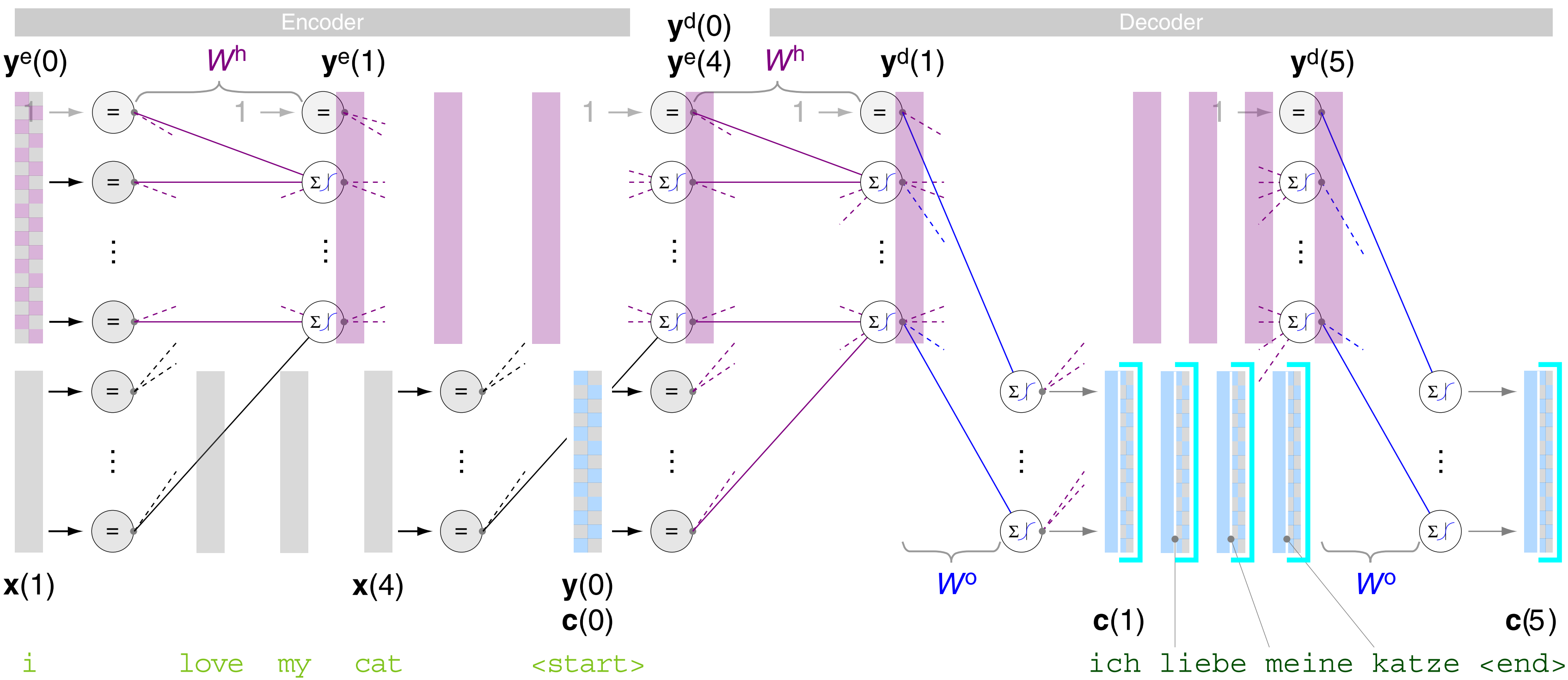
RNNs for Machine Translation

(S3) Sequence-to-Sequence Mapping with RNNs (continued)



Input:

$\mathbf{x}$, $[\mathbf{y}(1), \ldots, \mathbf{y}(4)]$

Output:

$$\mathbf{y}(t) = \boldsymbol{\sigma}_1\left(W^{\mathrm{o}}\,\mathbf{y}^{\mathrm{d}}(t)\right), t = 1, \ldots, 5$$

Hidden:

$$\mathbf{y}^{\mathrm{e}}(t) = \boldsymbol{\sigma}\left(W^{\mathrm{h}}\begin{pmatrix}\mathbf{y}^{\mathrm{e}}(t-1)\\ \mathbf{x}(t)\end{pmatrix}\right), t = 1, \ldots, 4$$

$$\mathbf{y}^{\mathrm{d}}(t) = \boldsymbol{\sigma}\left(W^{\mathrm{h}}\begin{pmatrix}\mathbf{y}^{\mathrm{d}}(t-1)\\ \mathbf{c}(t-1)\end{pmatrix}\right), t = 1, \ldots, 5$$

Target:

$[\mathbf{c}(1), \ldots, \mathbf{c}(5)]$

$\mathbf{c}(5) \mathrel{\widehat{=}}$ <end>

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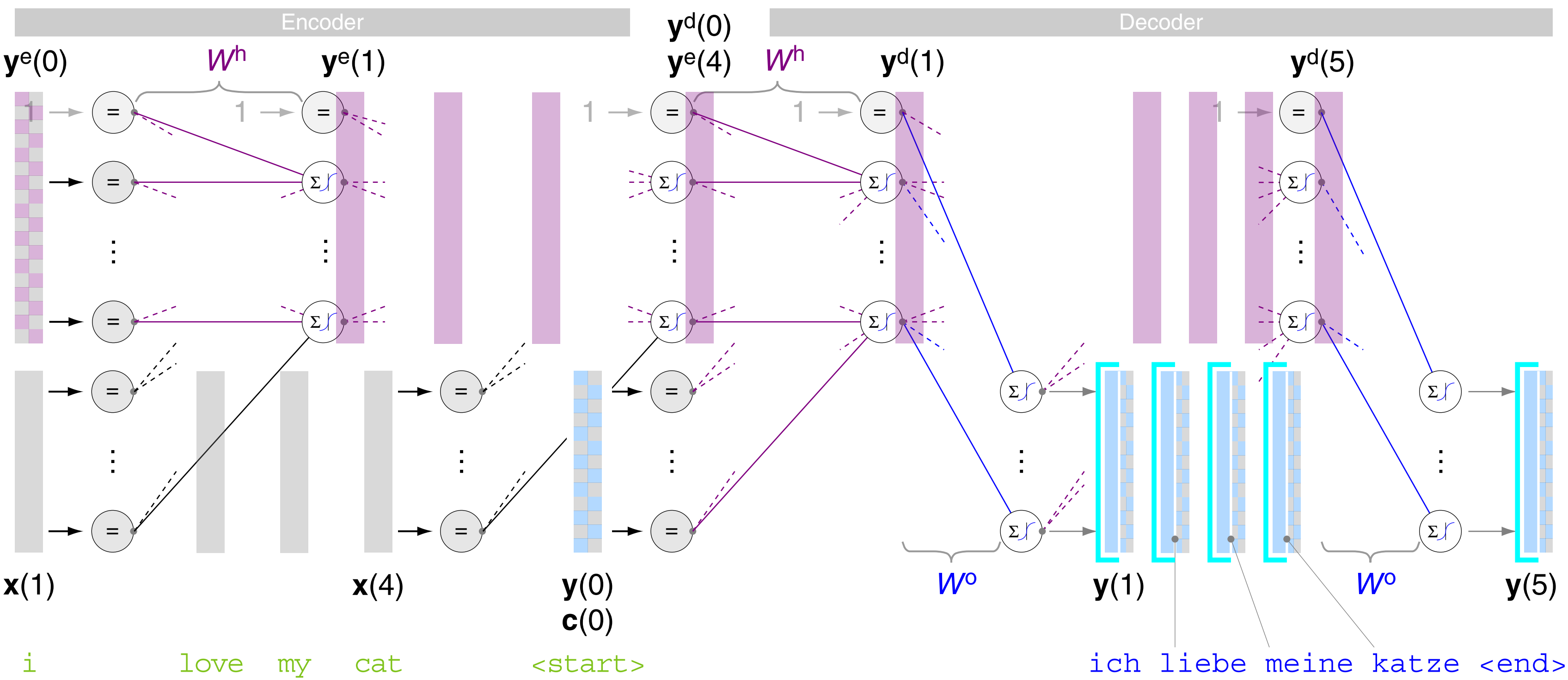
RNNs for Machine Translation

(S3) Sequence-to-Sequence Mapping with RNNs (continued)



Input:

$\mathbf{x}$, $[\mathbf{y}(1), \ldots, \mathbf{y}(4)]$

Output:

$$\mathbf{y}(t) = \boldsymbol{\sigma}_1\left(W^o\,\mathbf{y}^d(t)\right), t = 1, \ldots, 5$$

Hidden:

$$\mathbf{y}^e(t) = \boldsymbol{\sigma}\left(W^h\begin{pmatrix}\mathbf{y}^e(t-1)\\ \mathbf{x}(t)\end{pmatrix}\right), t = 1, \ldots, 4$$

$$\mathbf{y}^d(t) = \boldsymbol{\sigma}\left(W^h\begin{pmatrix}\mathbf{y}^d(t-1)\\ \mathbf{y}(t-1)\end{pmatrix}\right), t = 1, \ldots, 5$$

Target:

$[\mathbf{c}(1), \ldots, \mathbf{c}(5)]$

$\mathbf{c}(5) \mathrel{\widehat{=}}$ <end>

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Remarks:

- The final encoder hidden state, $\mathbf{y}^{\mathsf{e}}(T^{\mathsf{e}})$, represents the encoding of the source sentence. $\mathbf{y}^{\mathsf{e}}(T^{\mathsf{e}})$ is unified with the first decoder hidden state, $\mathbf{y}^{\mathsf{d}}(0)$.
- The encoder hidden state $\mathbf{y}^{\mathsf{e}}(t)$ represents the input sequence *up* to time step t, $[\mathbf{x}(1), \ldots, \mathbf{x}(t)]$.
- The decoder hidden state $\mathbf{y}^{\mathsf{d}}(t)$ represents the entire input sequence $[\mathbf{x}(1), \ldots, \mathbf{x}(T^{\mathsf{e}})]$, as well as the output sequence *up* to time step $t{-}1$, $[\mathbf{y}(1), \ldots, \mathbf{y}(t-1)]$.
- Note that, as before, we are given a model function $\mathbf{y}()$, which maps some input (actually, a *sequence* of feature vectors, $[\mathbf{x}(1), \ldots, \mathbf{x}(T^{\mathsf{e}})]$) to some output (a sequence of output vectors, $[\mathbf{y}(1), \ldots, \mathbf{y}(T^{\mathsf{d}}])$.

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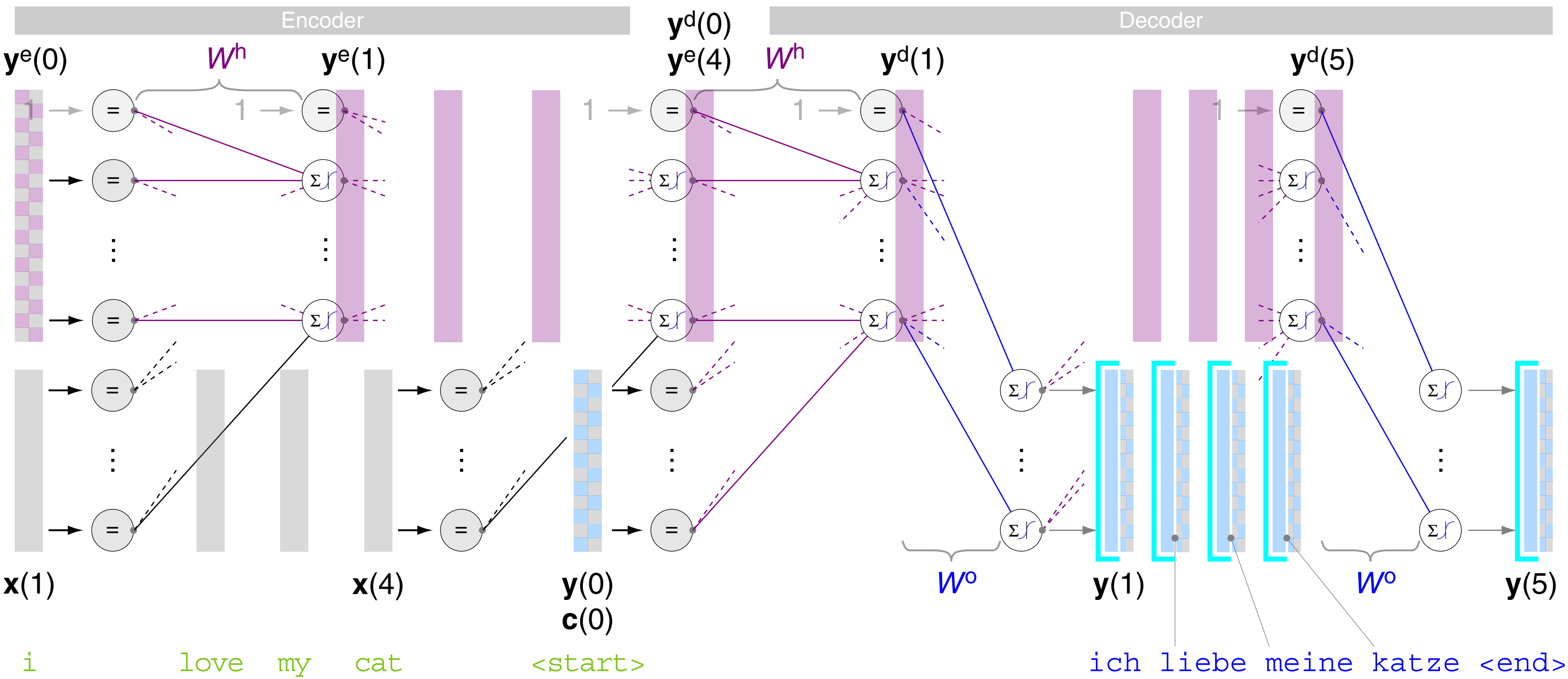
RNNs for Machine Translation

Sequence-to-Sequence RNNs are Conditional Language Models



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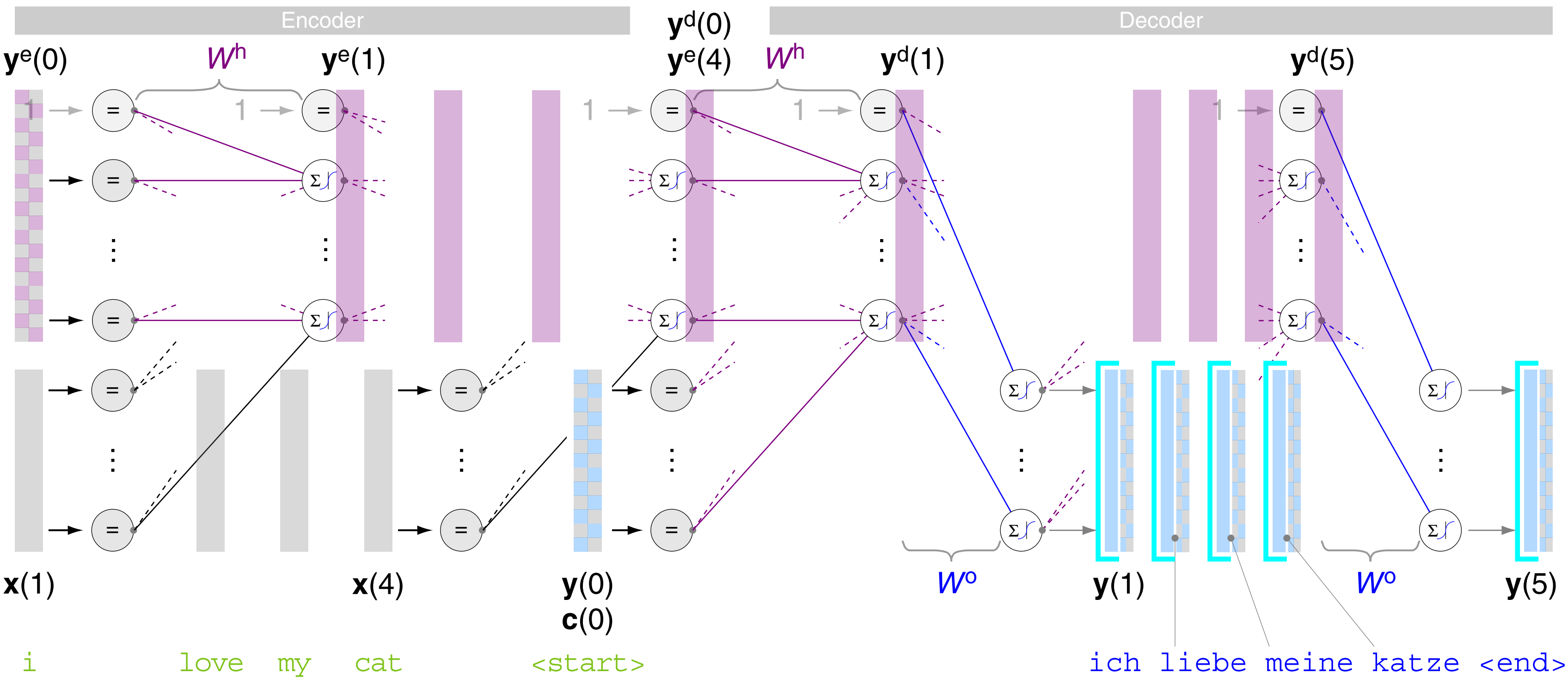
RNNs for Machine Translation

Sequence-to-Sequence RNNs are Conditional Language Models (continued)



The sequence-to-sequence RNN directly calculates $p(y \mid x)$:

$$p(y \mid x) \;=\; p(y_1 \mid x) \cdot p(y_2 \mid y_1, x) \cdot p(y_3 \mid y_1, y_2, x) \cdot p(y_4 \mid y_1, y_2, y_3, x)$$

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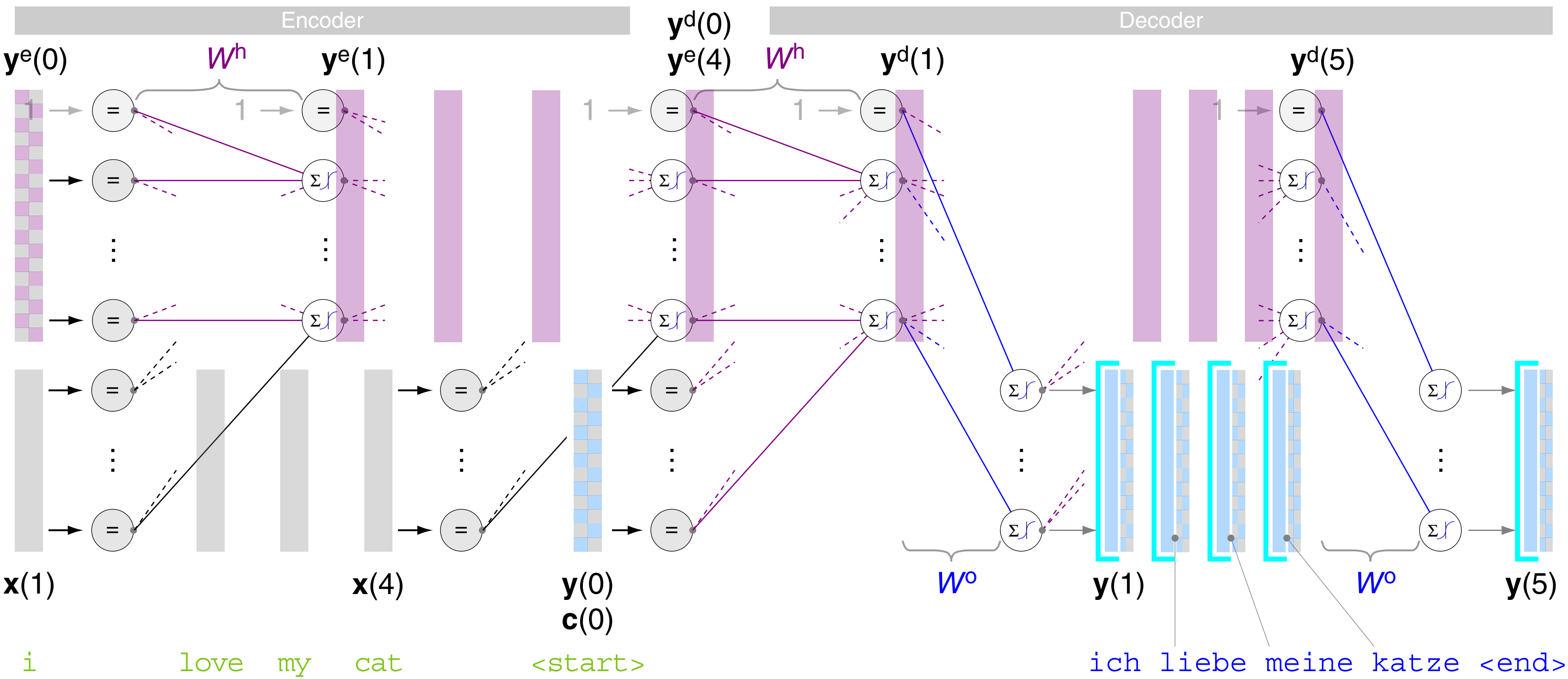
RNNs for Machine Translation

Sequence-to-Sequence RNNs are Conditional Language Models (continued)



The sequence-to-sequence RNN directly calculates $p(y \mid x)$:

$$p(y \mid x) \;\equiv\; p(\mathbf{y}(1), \ldots, \mathbf{y}(5) \mid \mathbf{x}, \mathbf{y}(0)), \qquad \mathbf{x} := \mathbf{x}(1), \mathbf{x}(2), \mathbf{x}(3), \mathbf{x}(4)$$

$$= \; p(\mathbf{y}(1) \mid \mathbf{x}, \mathbf{y}(0)) \;\cdot\; p(\mathbf{y}(2) \mid \mathbf{x}, \mathbf{y}(0), \mathbf{y}(1)) \;\cdot \ldots \cdot\; p(\mathbf{y}(5) \mid \mathbf{x}, \mathbf{y}(0), \ldots, \mathbf{y}(4))$$

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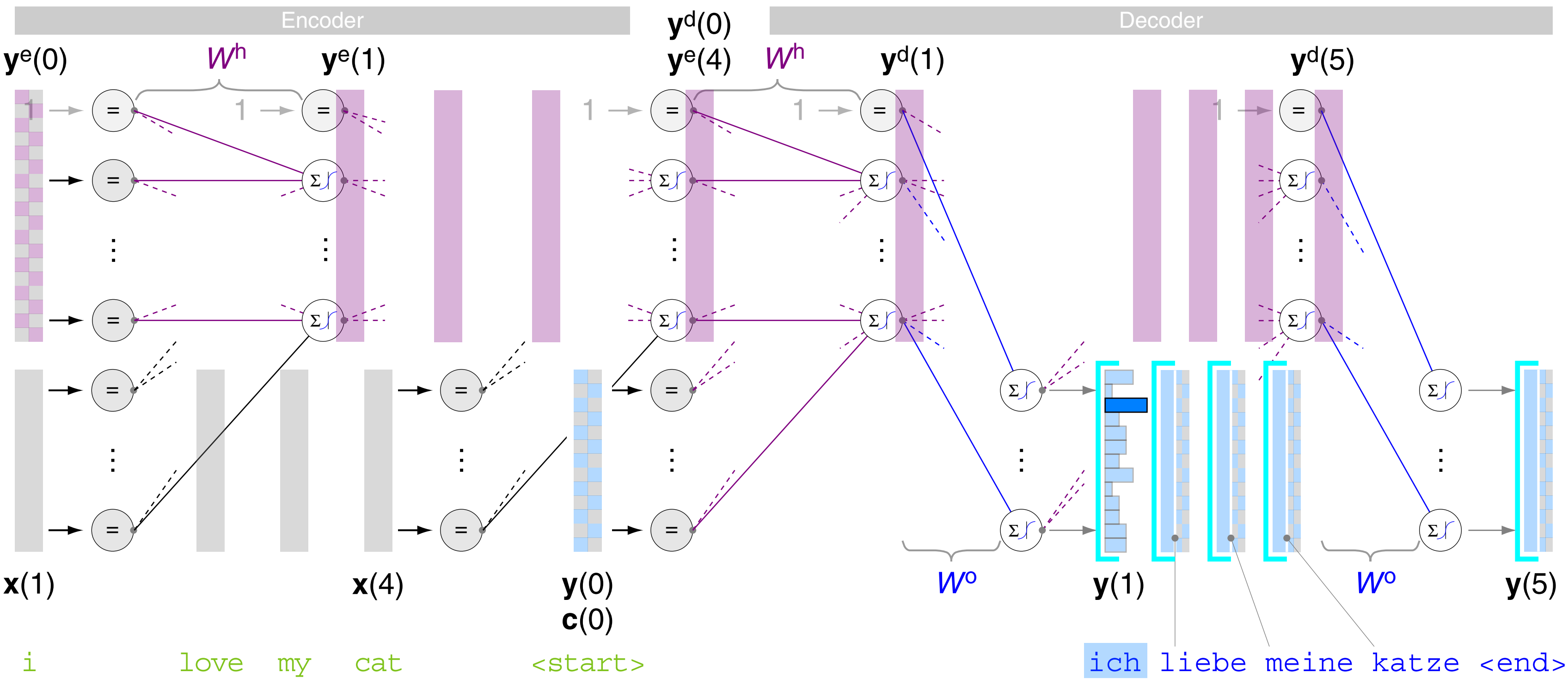
RNNs for Machine Translation

Sequence-to-Sequence RNNs are Conditional Language Models (continued)



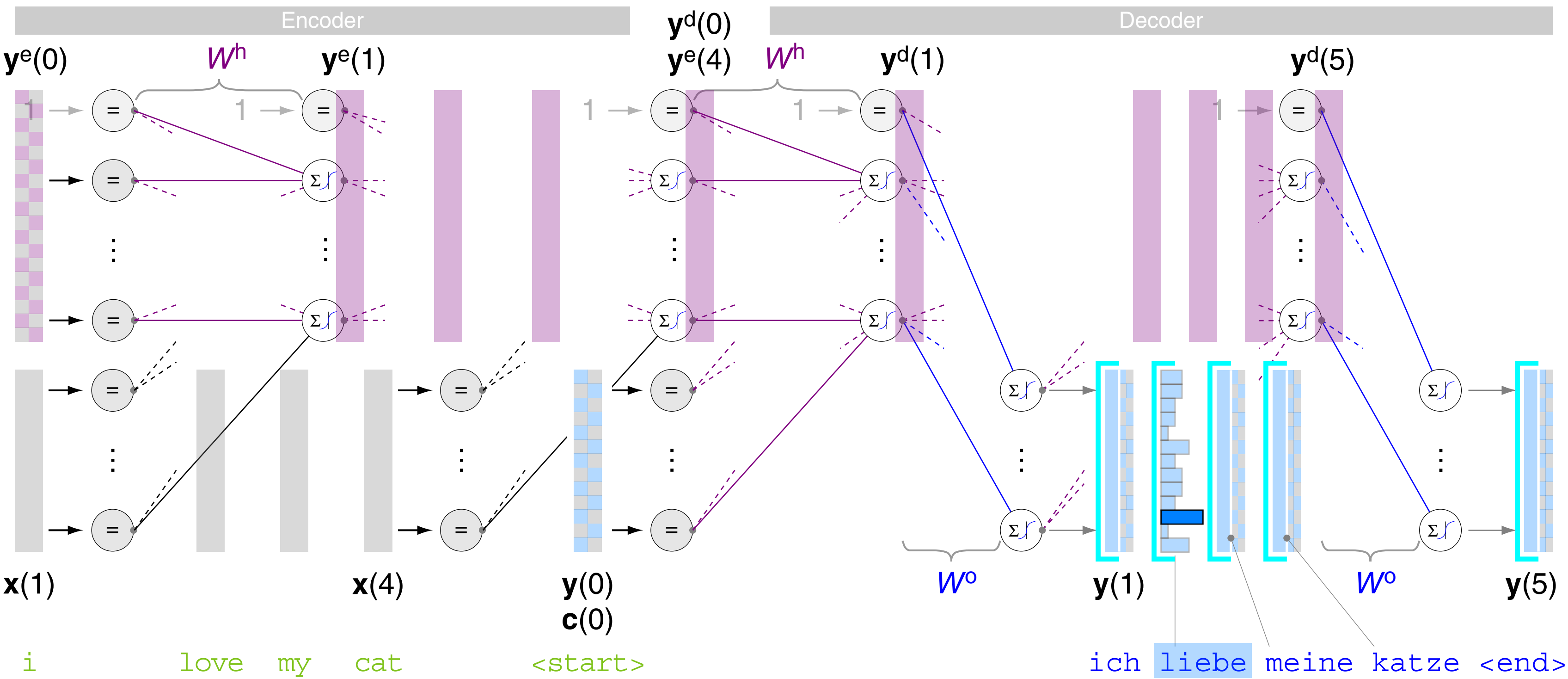
The sequence-to-sequence RNN directly calculates $p(y \mid x)$:

$$p(y \mid x) \equiv p(\mathbf{y}(1), \ldots, \mathbf{y}(5) \mid \mathbf{x}, \mathbf{y}(0)), \qquad \mathbf{x} := \mathbf{x}(1), \mathbf{x}(2), \mathbf{x}(3), \mathbf{x}(4)$$

$$= \boxed{p(\mathbf{y}(1) \mid \mathbf{x}, \mathbf{y}(0))} \cdot p(\mathbf{y}(2) \mid \mathbf{x}, \mathbf{y}(0), \mathbf{y}(1)) \cdot \ldots \cdot p(\mathbf{y}(5) \mid \mathbf{x}, \mathbf{y}(0), \ldots, \mathbf{y}(4))$$

RNNs for Machine Translation

Sequence-to-Sequence RNNs are Conditional Language Models (continued)



The sequence-to-sequence RNN directly calculates $p(y \mid x)$:

$$p(y \mid x) \;\equiv\; p(\mathbf{y}(1), \ldots, \mathbf{y}(5) \mid \mathbf{x}, \mathbf{y}(0)), \qquad \mathbf{x} := \mathbf{x}(1), \mathbf{x}(2), \mathbf{x}(3), \mathbf{x}(4)$$

$$= \; p(\mathbf{y}(1) \mid \mathbf{x}, \mathbf{y}(0)) \cdot \boxed{p(\mathbf{y}(2) \mid \mathbf{x}, \mathbf{y}(0), \mathbf{y}(1))} \cdot \ldots \cdot p(\mathbf{y}(5) \mid \mathbf{x}, \mathbf{y}(0), \ldots, \mathbf{y}(4))$$

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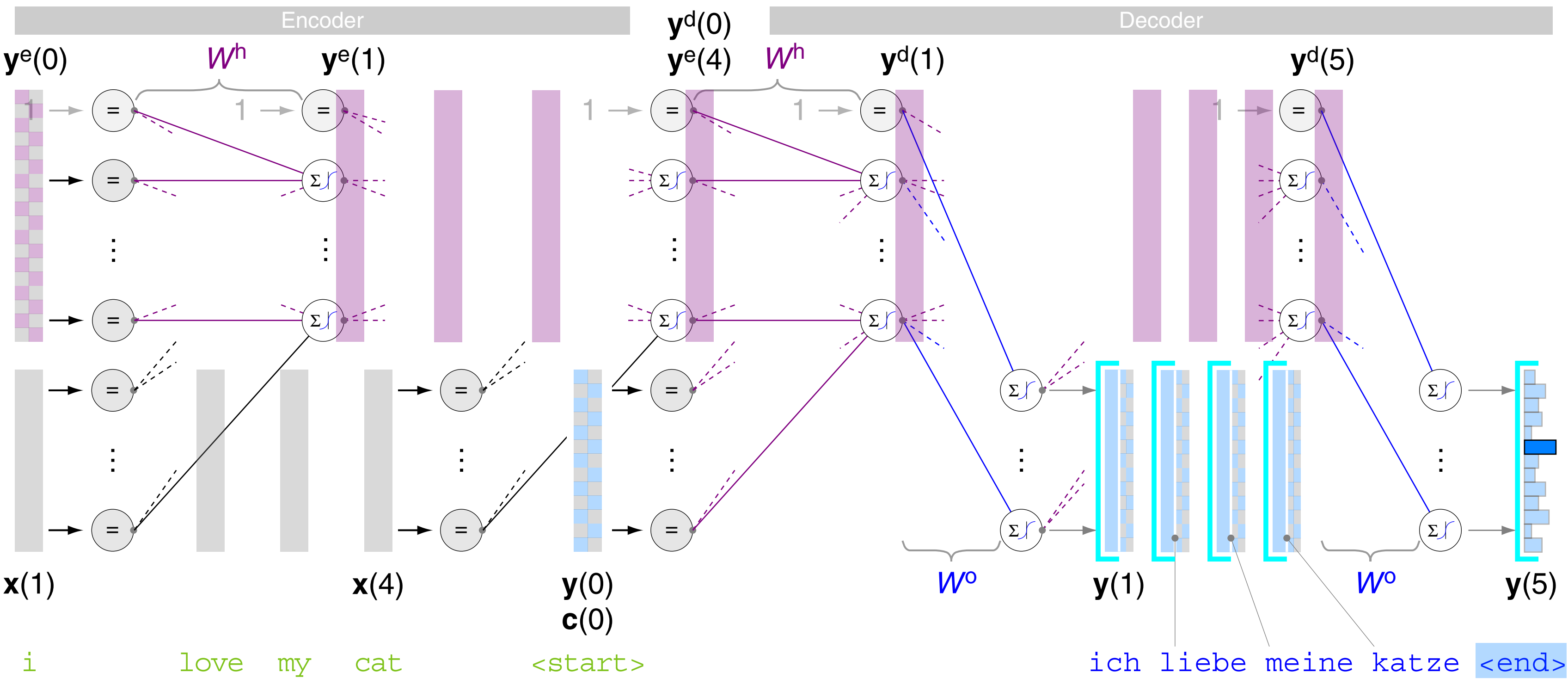
RNNs for Machine Translation

Sequence-to-Sequence RNNs are Conditional Language Models (continued)



The sequence-to-sequence RNN directly calculates $p(y \mid x)$:

$$p(y \mid x) \;\equiv\; p(\mathbf{y}(1), \ldots, \mathbf{y}(5) \mid \mathbf{x}, \mathbf{y}(0)), \qquad \mathbf{x} := \mathbf{x}(1), \mathbf{x}(2), \mathbf{x}(3), \mathbf{x}(4)$$

$$= \; p(\mathbf{y}(1) \mid \mathbf{x}, \mathbf{y}(0)) \cdot p(\mathbf{y}(2) \mid \mathbf{x}, \mathbf{y}(0), \mathbf{y}(1)) \cdot \ldots \cdot \boxed{p(\mathbf{y}(5) \mid \mathbf{x}, \mathbf{y}(0), \ldots, \mathbf{y}(4))}$$

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Remarks:

- Each output vector $\mathbf{y}(t)$ corresponds to a probability distribution over Vocabulary[d] (recall the $\boldsymbol{\sigma}_1$-function). Here, the illustration of generation (aka decoding) steps shows an argmax-operation on each $\mathbf{y}(t)$, called "greedy decoding" : the word with the highest probability is chosen.

- To maximize $\prod_{t=1}^{\tau} p\left(\mathbf{y}(t) \mid \mathbf{x}, \mathbf{y}(0), \ldots, \mathbf{y}(t-1)\right)$, a complete search in the space of all sequences (target sentences) that can be generated is necessary, which is computationally intractable. Instead, heuristic search such as beam search is applied, where a beam size around 5 to 10 has shown good results in practice.

  The beam size is the number of generated successors in each decoding step; they are added to the OPEN list of the heuristic search algorithm. [Course on Search Algorithms]

- Sequence-to-sequence RNNs can be "stacked", this way forming a multilayer RNN, which is able to compute more complex representations. The idea is that the lower (higher) RNNs should compute lower-level (higher-level) features.

  Practice has shown that 2-4 layers are useful for neural machine translation, while transformer-based networks are typically deeper and comprise 12-24 layers.
  [Manning 2021, lecture CS224N]

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