Natural Language Processing (CS-472) Spring-2023

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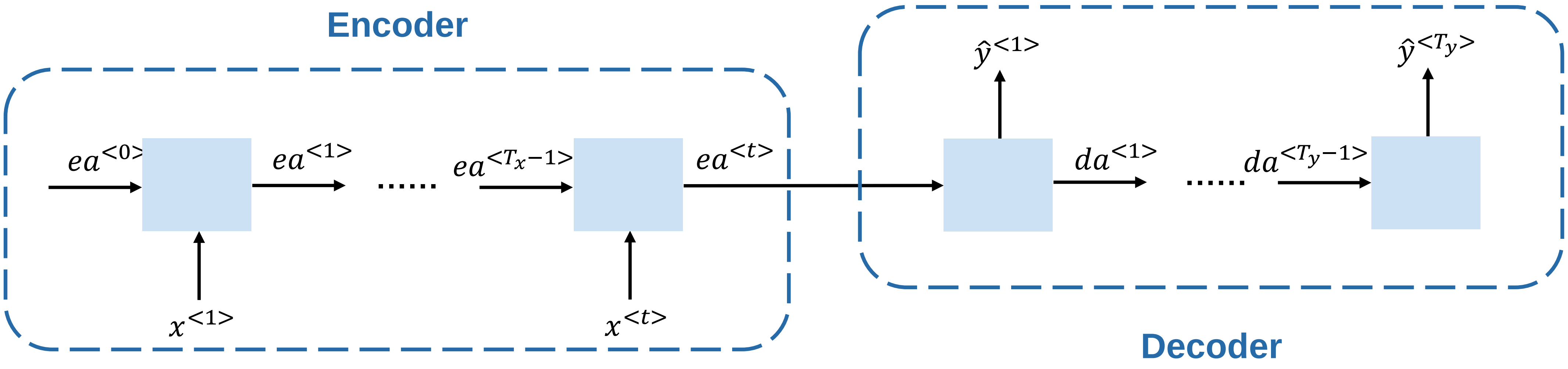
Overview of this week’s lecture

Machine Translation

- Statistical machine translation
- Neural network based machine translation
- Attention in seq2seq models

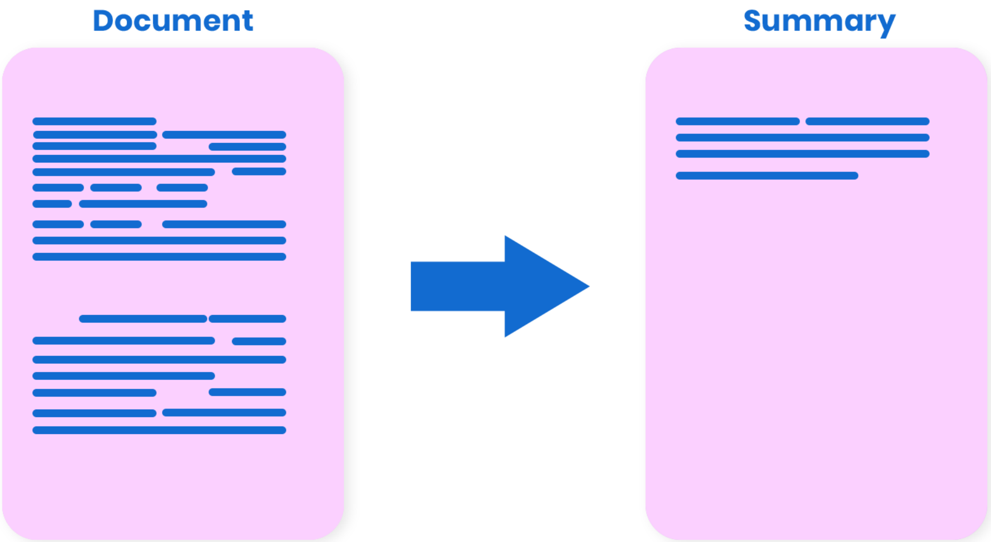
seq2seq models take sequential inputs and generate sequential outputs



Many-to-Many V2

seq2seq models are quite versatile

- Many other NLP tasks can be phrase as seq2seq problems.
  - Summarisation



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  - Dialogue

	Utterance	Dialogue act
U:	Hi, I am looking for somewhere to eat.	`hello(task = find,type=restaurant)`
S:	You are looking for a restaurant. What type of food do you like?	`confreq(type = restaurant, food)`
U:	I'd like an Italian somewhere near the museum.	`inform(food = Italian, near=museum)`
S:	Roma is a nice Italian restaurant near the museum.	`inform(name = "Roma", type = restaurant, food = Italian, near = museum)`
U:	Is it reasonably priced?	`confirm(pricerange = moderate)`
S:	Yes, Roma is in the moderate price range.	`affirm(name = "Roma", pricerange = moderate)`
U:	What is the phone number?	`request(phone)`
S:	The number of Roma is 385456.	`inform(name = "Roma", phone = "385456")`
U:	Ok, thank you goodbye.	bye()

Figure 26.13 A sample dialogue from the HIS System of Young et al. (2010) using the dialogue acts in Fig. 26.12.

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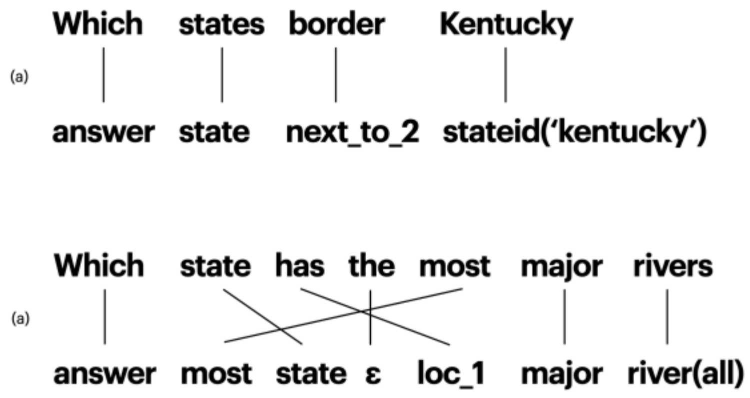
  - Semantic Parsing



https://arxiv.org/pdf/2205.08288.pdf

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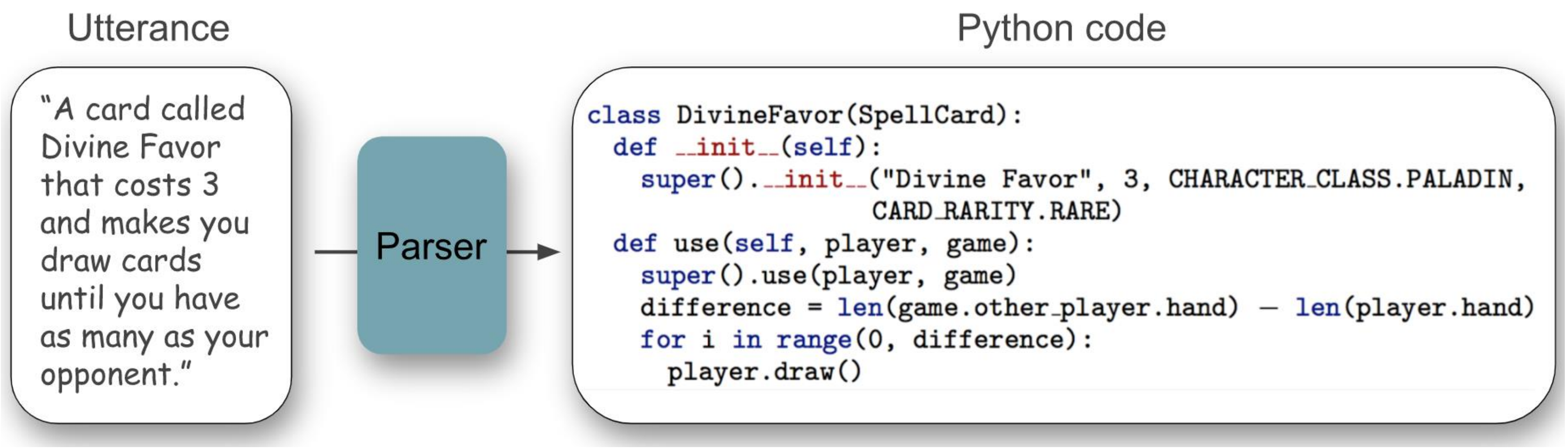

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- Many other NLP tasks can be phrase as seq2seq problems.
  - Summarisation
  - Dialogue
  - Semantic Parsing
  - Code Generation
  - Language Translation

Diese Woche haben wir einen zusätzlichen Vortrag.

This week we are having on additional lecture.

Language translation is one of the prime use-cases of seq2seq models

- The task of language translation requires converting an input sentence $\boldsymbol{x}$ from a source language to an output sentence $\boldsymbol{y}$ in the target language preserving the semantic information.

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The spirit is willing but the flesh is weak.	→	The liquor is good but the meat is spoiled.
Out of sight, out of mind.	→	Invisible, idiot.

The need for machine translation emerged during the cold war

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    1. Statistical Methods
    2. Neural Network based Methods

- Suppose we are translating from English to German.

Statistical Machine Translation (SMT) learns probabilistic language models

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- The task of SMT can be formulated as,
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  - However, $P(e)$ does not depend on the German sentence, it can be considered as a constant.

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  - $P(g)$: A German language model.
    - Ensures fluency of German sentences.
    - Checks if the output sentence conforms to German grammar and sentence structure.
  - $argmax_g$: Finds the sentence g that maximises this probability.

How to learn translation model?

- The model $P(e|g)$ can be further divided into two components.

$$P(e|g) = P(e,a|g)$$

  - Here, a represent alignment (correspondence) between German and English words.

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Japan shaken by two new quakes

Japan von zwei neuen Beben erschüttert

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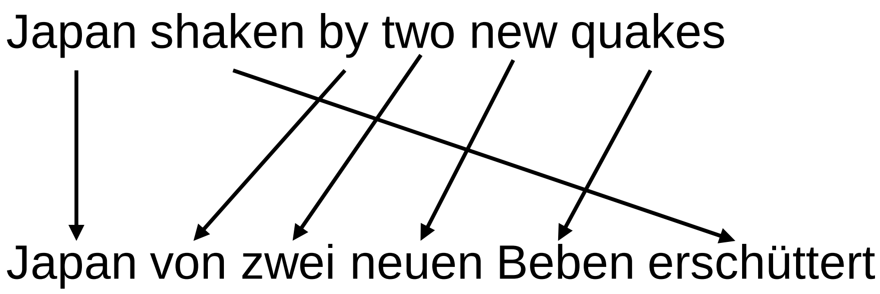

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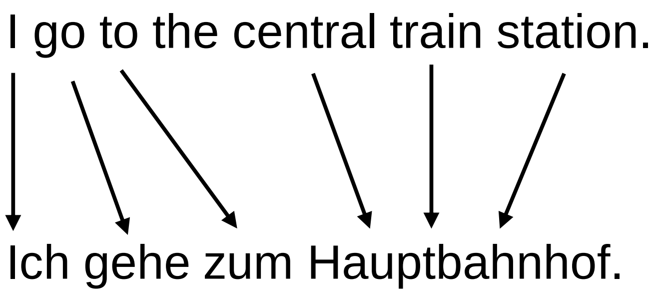

Many to One Alignment

Alignment is complex

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He has a face in need of a fist.

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Er hat Backpfeifengesicht

He has a face in need of a fist.

- There can also be many to many alignment at phrase level.

Er geht ja nicht nach hause

He is not going home

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- Each language required different features to be captured.
  - Many extra resources needed to be compiled and maintained.
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- Depended on manual labour which was not reusable.
  - For every language pair, the whole process needs to be repeated.

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$\underbrace{\text{Ich} \quad \text{gehe} \quad \text{zum Hauptbahnhof}}_{\textbf{Source sentence (input)}}$

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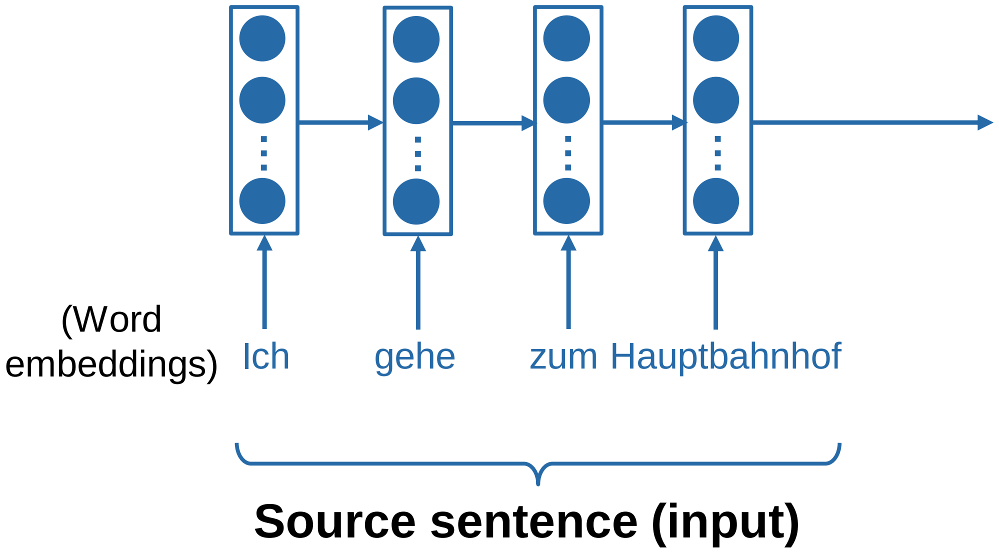

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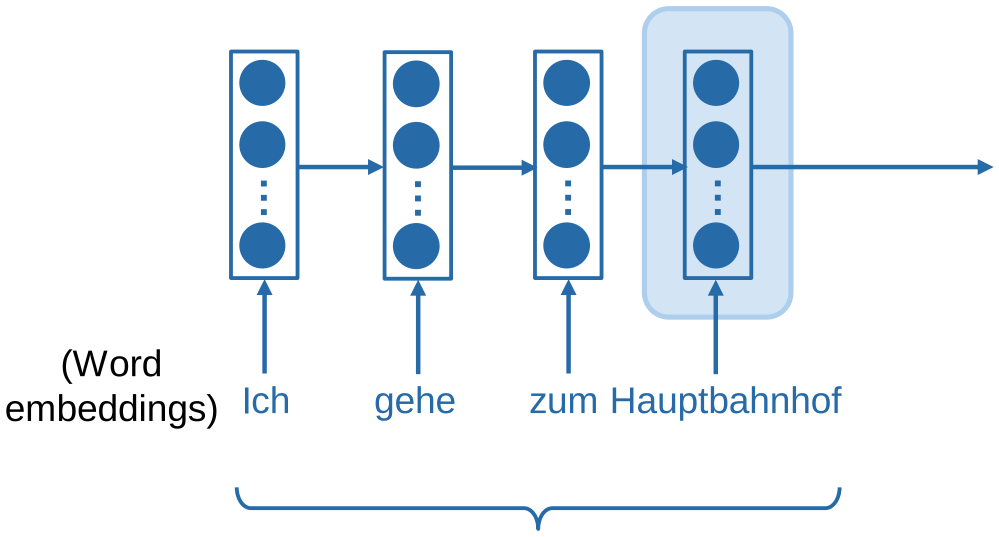
The crux of the whole input sentence is encoded here



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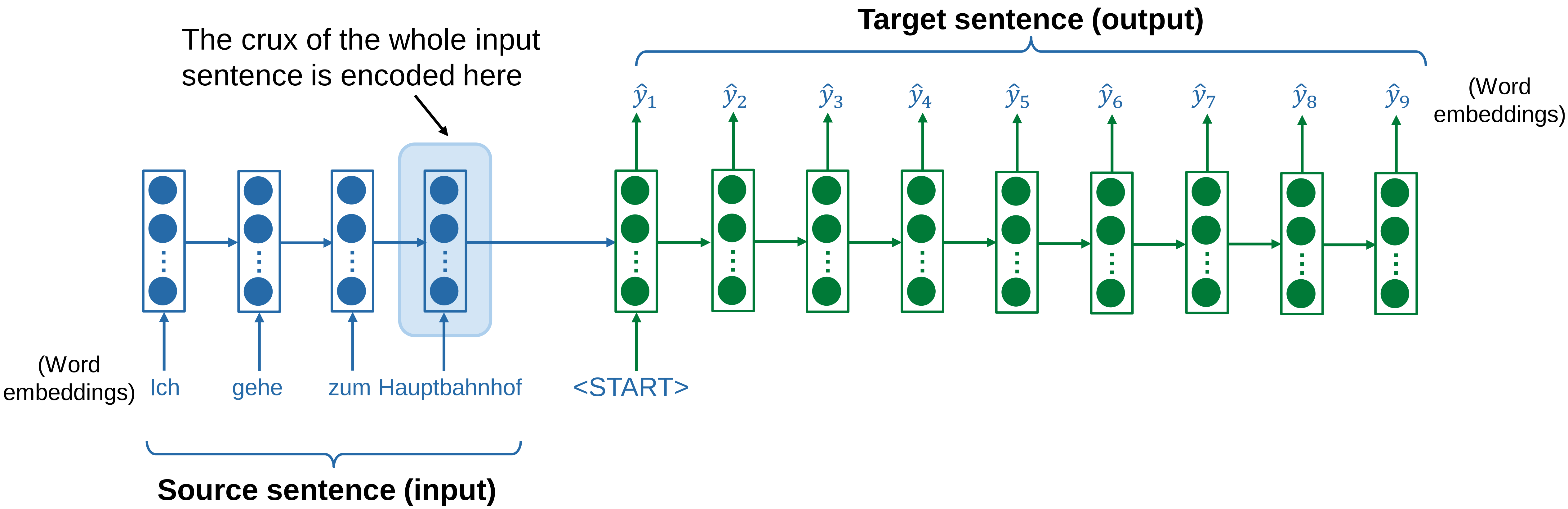

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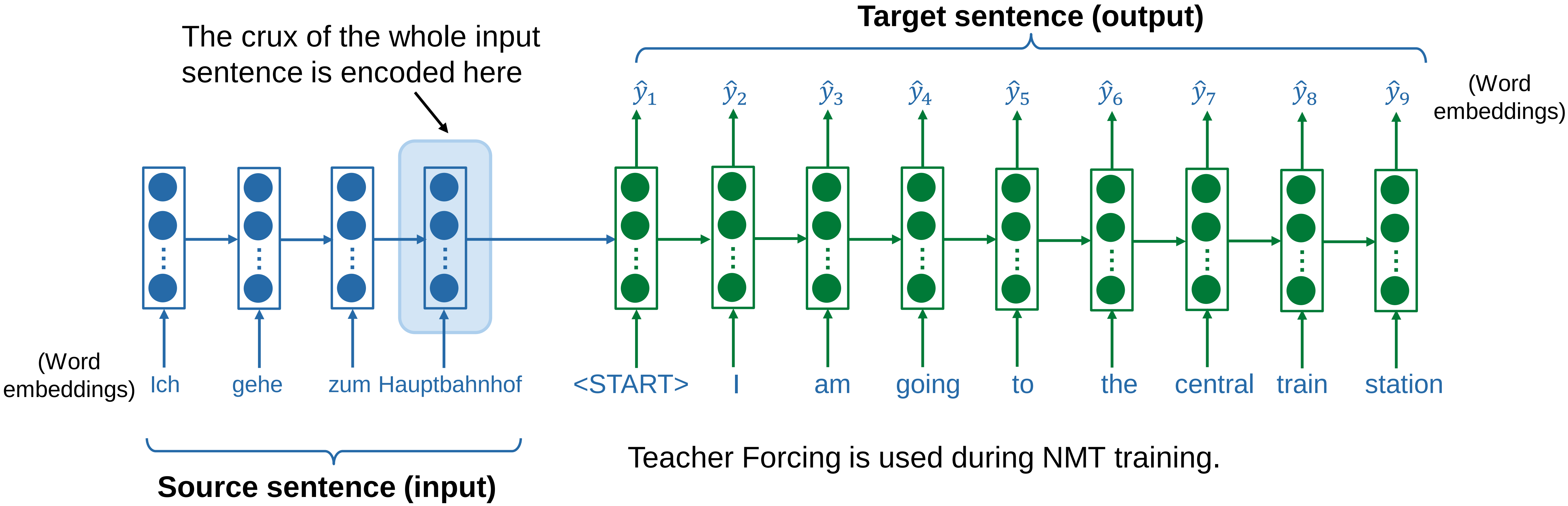

Teacher Forcing is used during NMT training.

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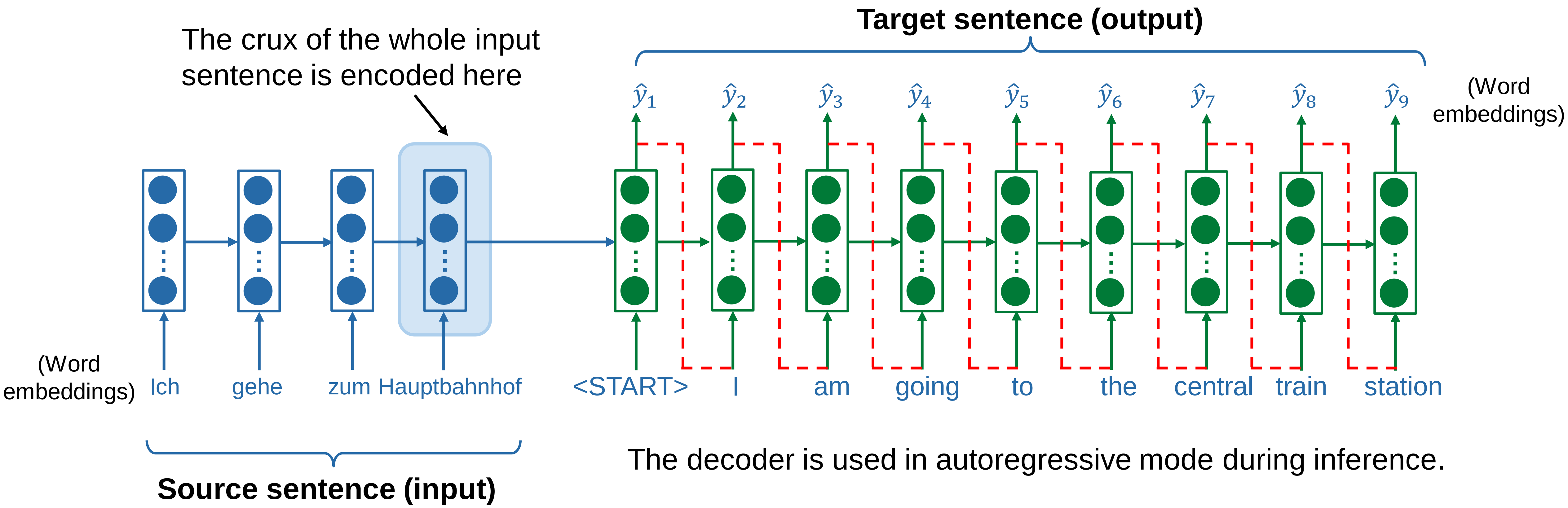
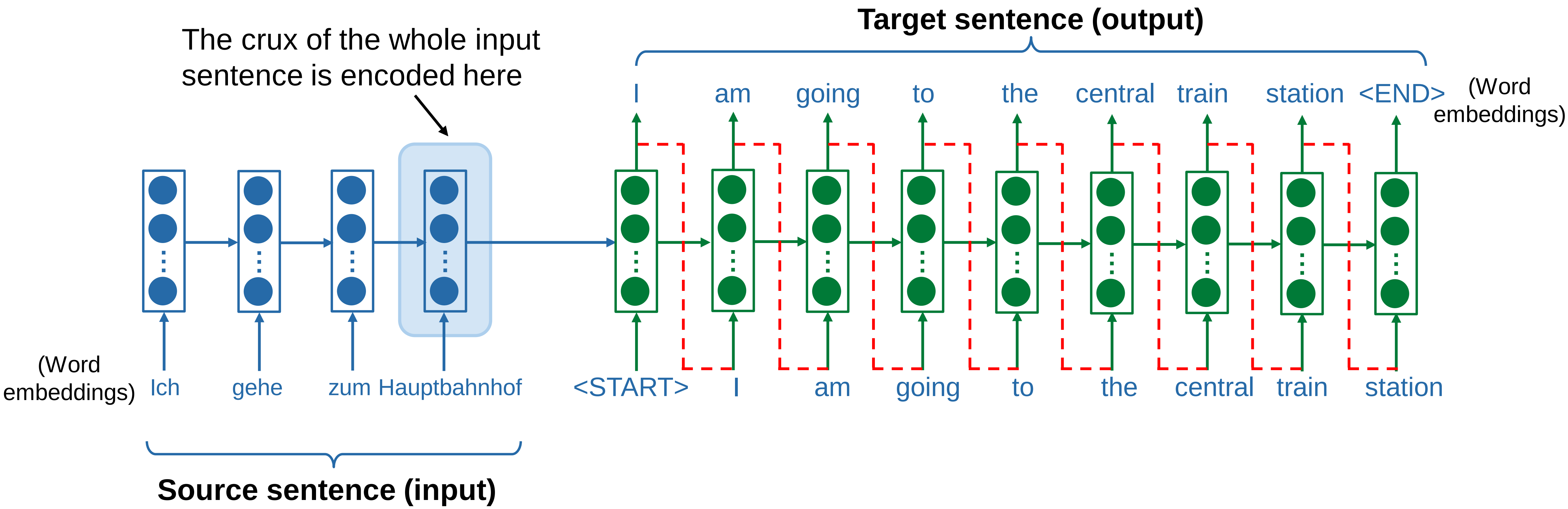


The decoder is used in autoregressive mode during inference.

Neural Machine Translation (NMT) made its entry in 2014

- Decoder generates target language sentence conditioned on the encoding of the source sentence.



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$$P(g|e) = P(g_1|e)P(g_2|g_1, e)P(g_3|g_1, g_2, e) \dots P(g_T|g_1, g_2, \dots g_{T-1}, e)$$

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- No need to break down $P(g|e)$ into smaller components as in SMT.

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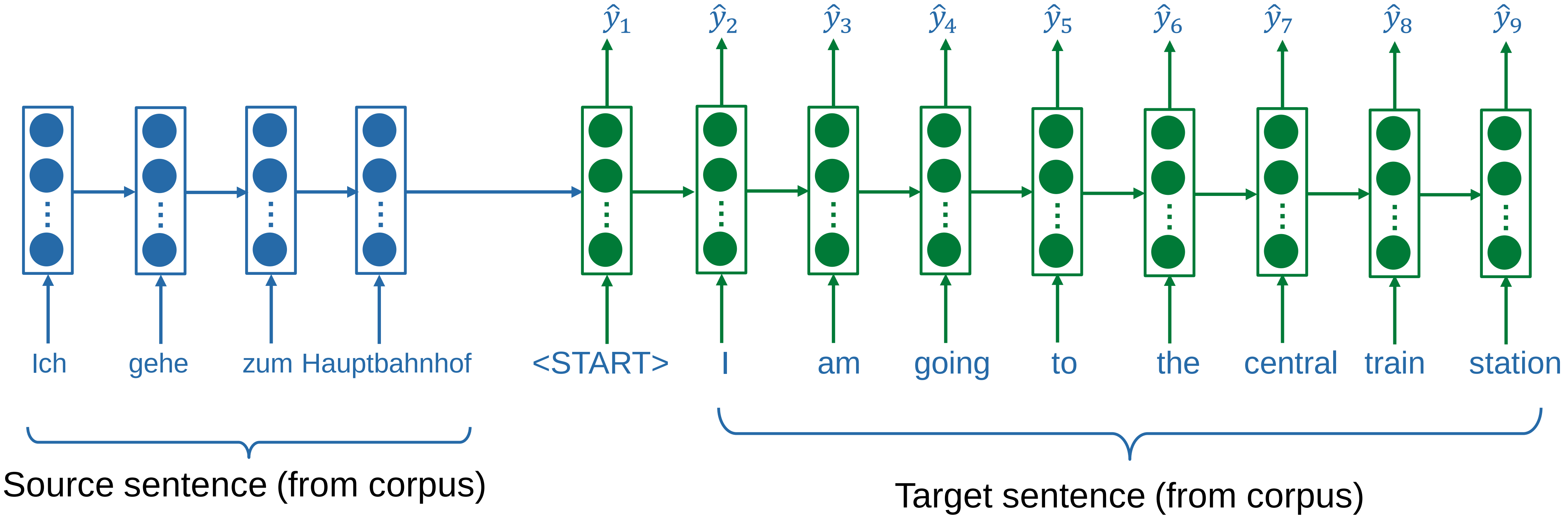

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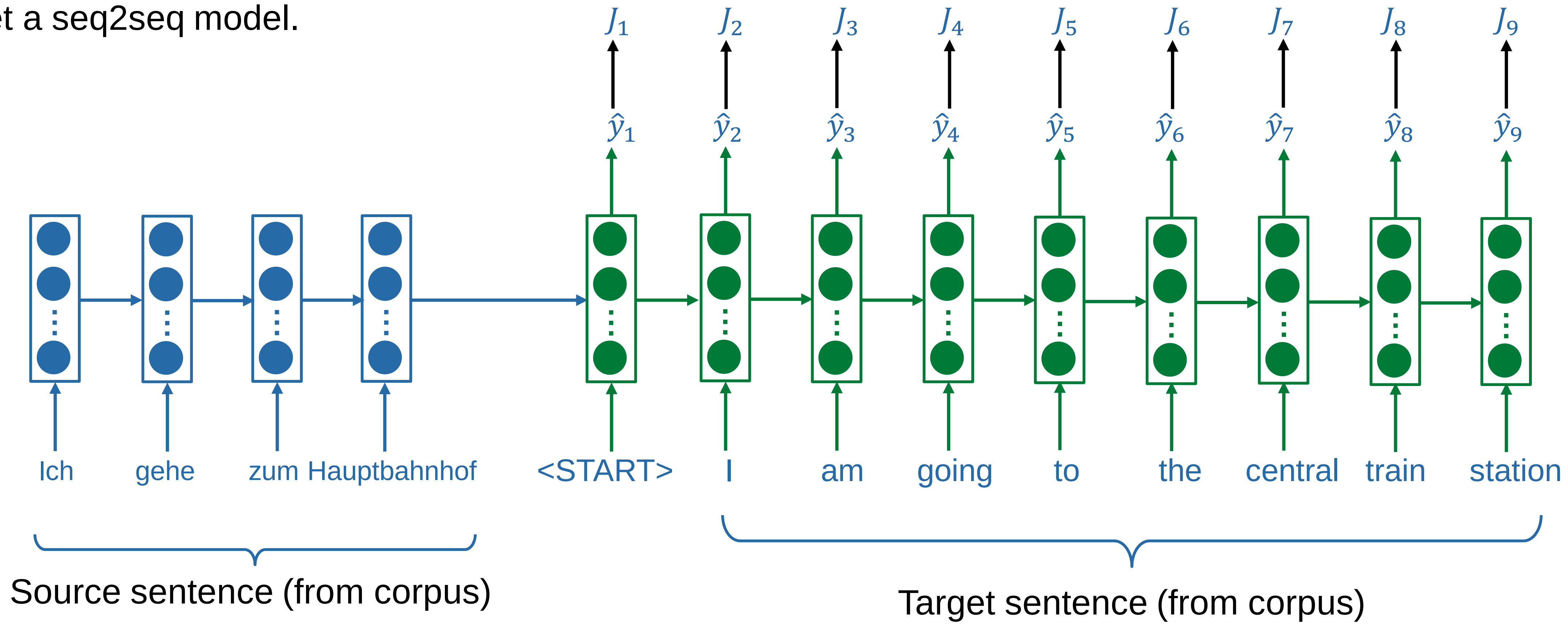

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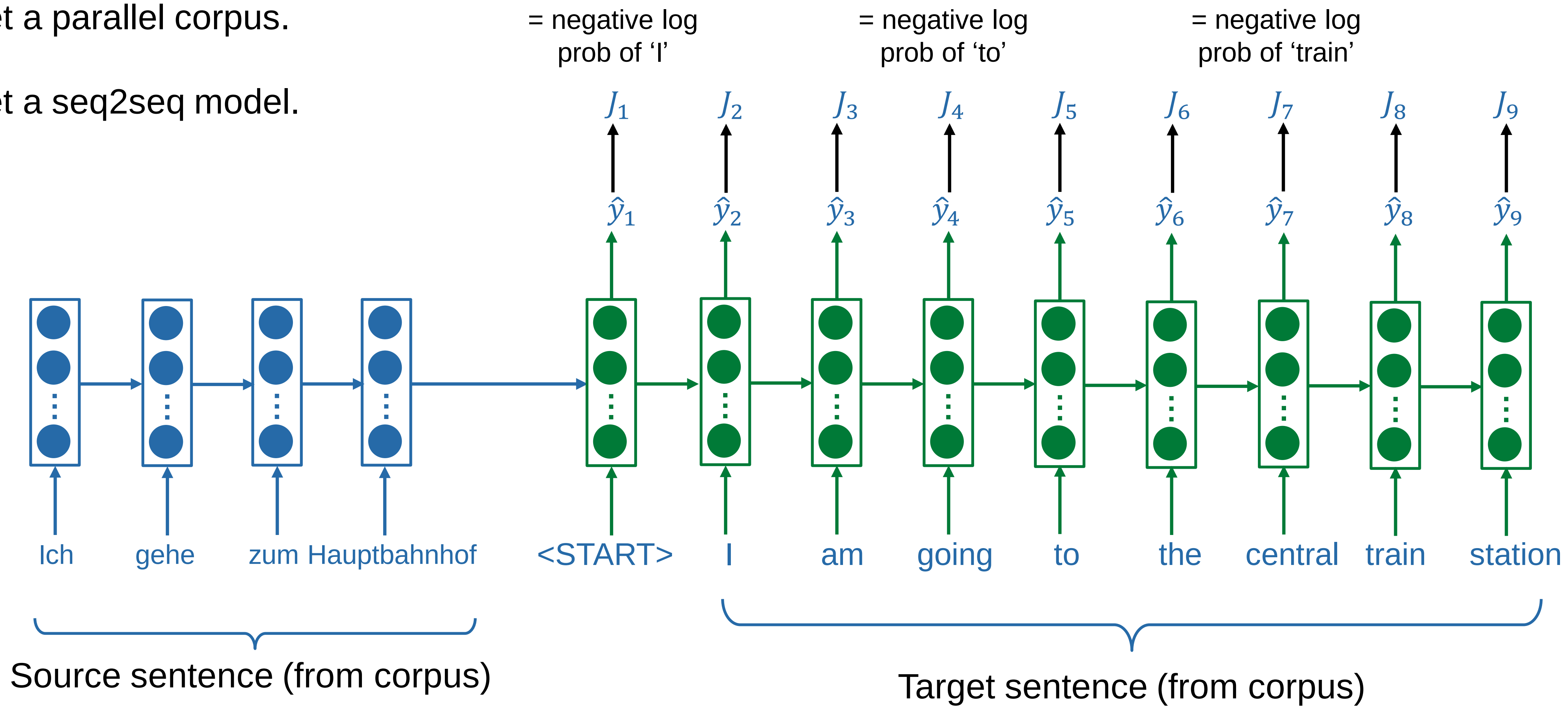

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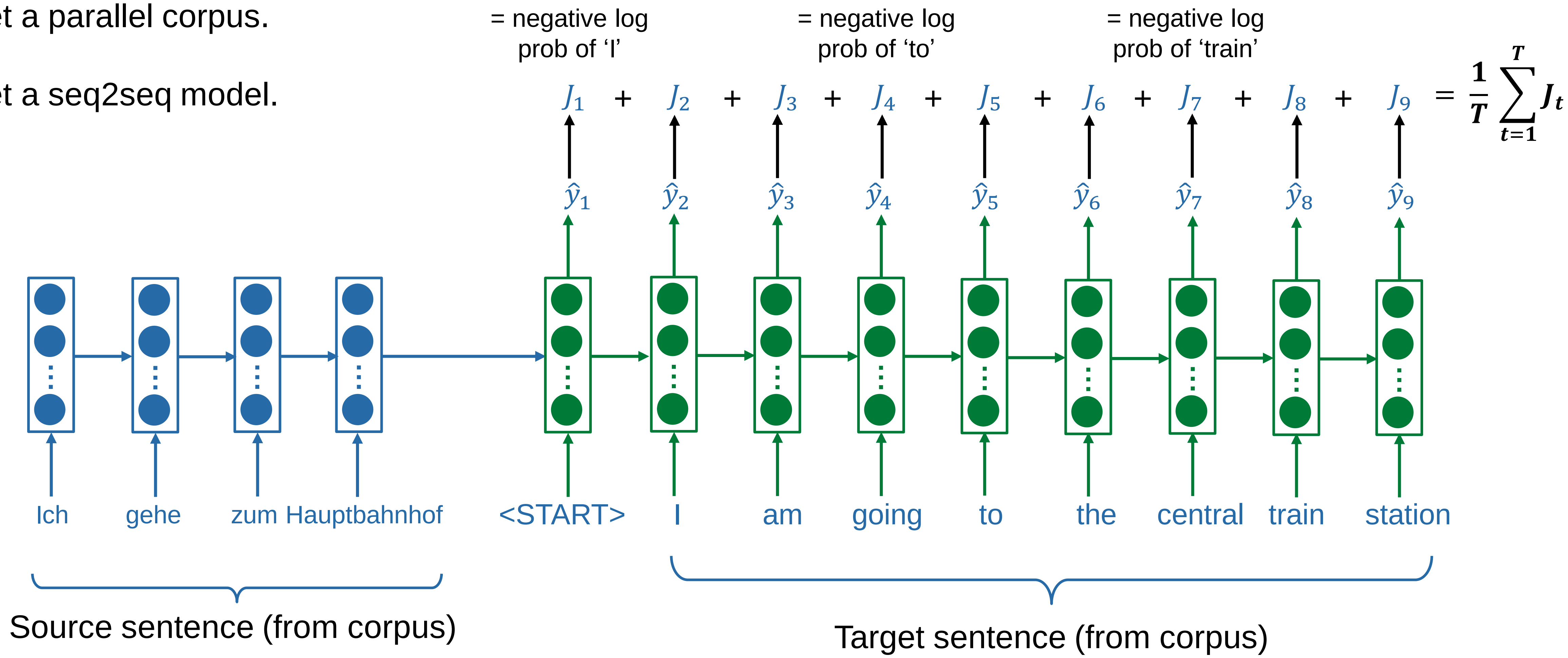

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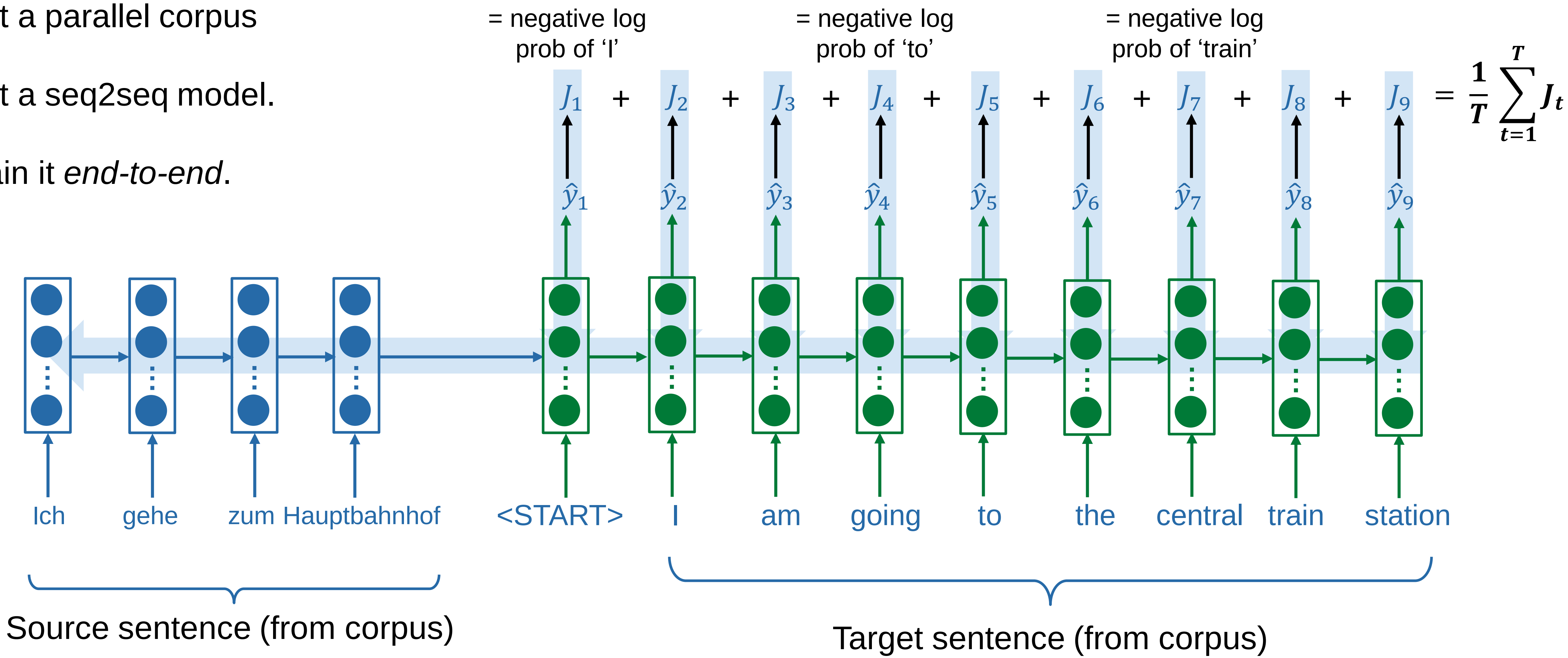
- Train it *end-to-end*.



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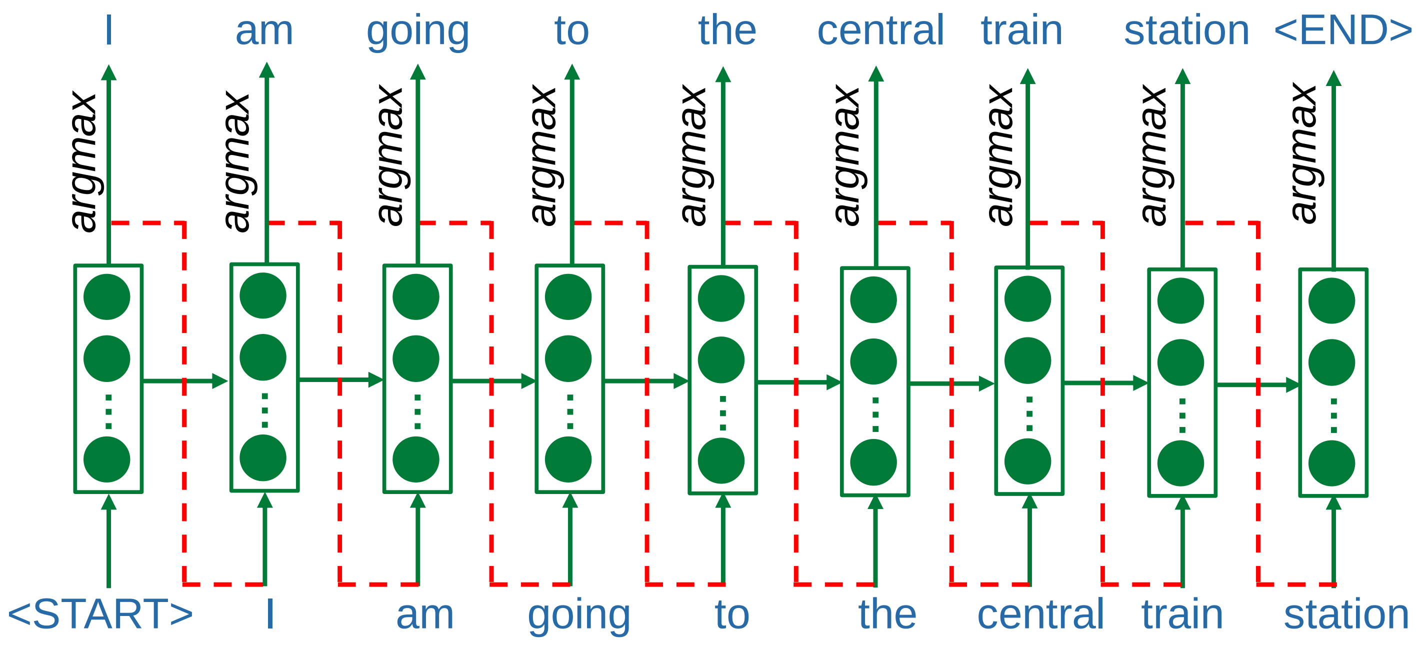

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  - Exhaustive Search? Compute all possible sequences.
    - At each time step t of decoder, V^t partial translations are tracked, where V is vocabulary size.
    - This results in $O\ (V^T)$ complexity which is far too expensive.

Beam search decoding provides inexpensive way to find suitable translation

- At each time step, keep track of k most likely partial translations (hypotheses).
  - k is the beam size, a hyperparameter whose value may be determined heuristically.
  - k determines the size of the search space.

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  - Each hypothesis has a suitability score defined as

$$score(\hat{y}^{<1>}, \hat{y}^{<2>}, \dots, \hat{y}^{<t>}) = \sum_{i=0}^{t} \log P_{LM}\,(\hat{y}^{i} | \hat{y}^{<1>}, \hat{y}^{<2>}, \dots, \hat{y}^{<i-1>}, x)$$

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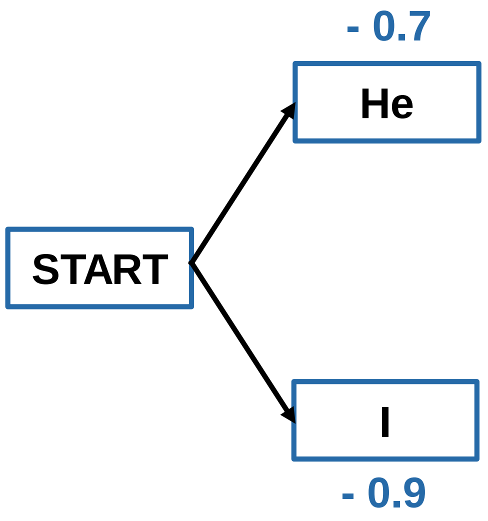
- **Note:** Scores of all hypotheses will be negative. High scores means more suitable hypothesis.
- **Caution:** Beam search is not guaranteed to find the optimal solution. But it’s efficient.

Let’s take an example of beam search

- For $k = 2$, and an example target sentence “***He hit me with a stick***”.

$score(He) = log\ P_{LM}(He| < START >)$



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$$score(He\ hit) = log\ P_{LM}(He| < START >) + log\ P_{LM}(hit| < START > He)$$

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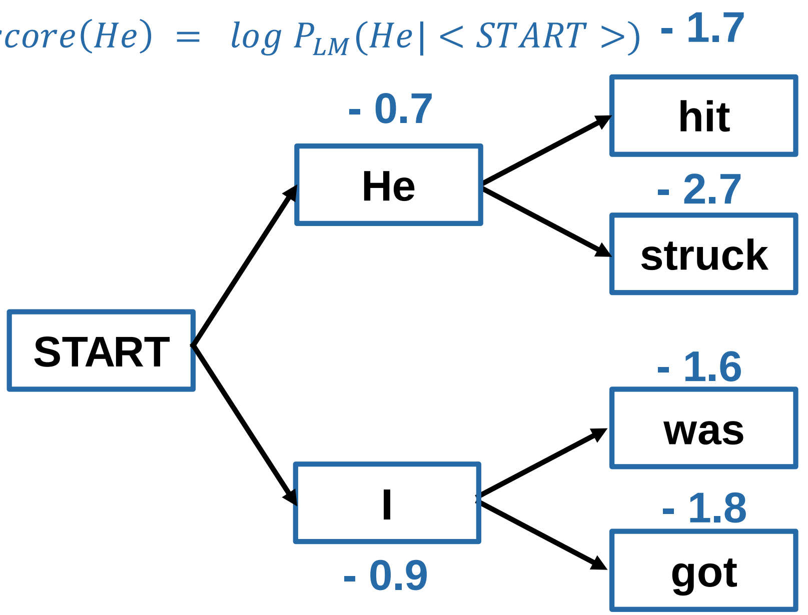
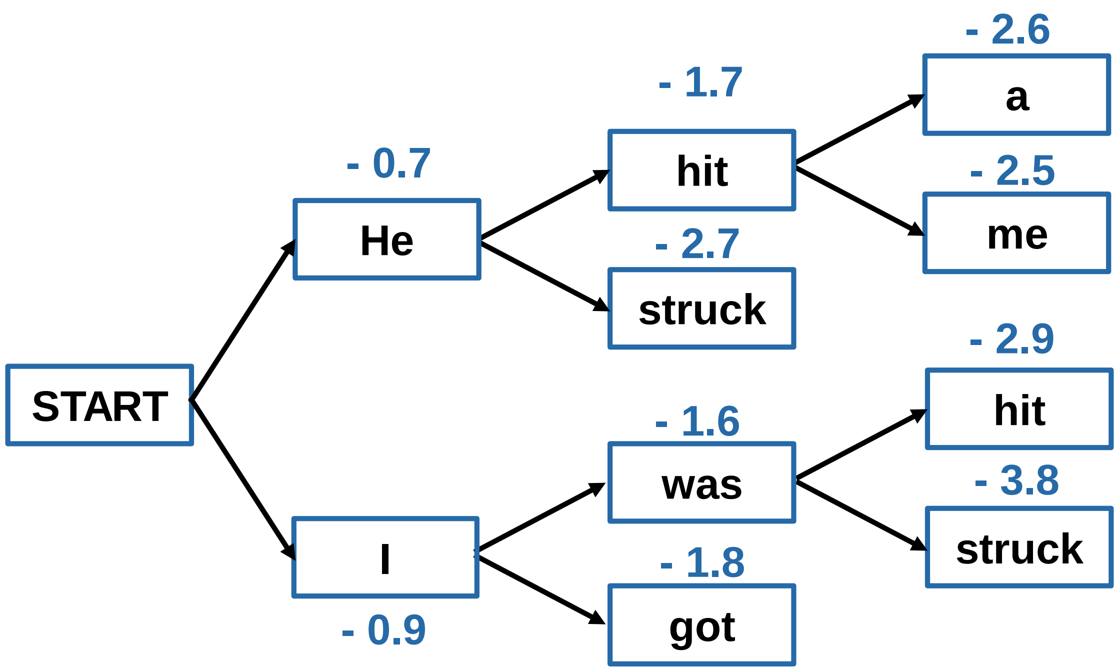


$$score(I) = log\ P_{LM}(I| < START >)$$

$$score(I\ got) = log\ P_{LM}(I| < START >) + log\ P_{LM}(got| < START > I)$$

Let's take an example of beam search

- For $k = 2$, and an example target sentence "***He hit me with a stick***".



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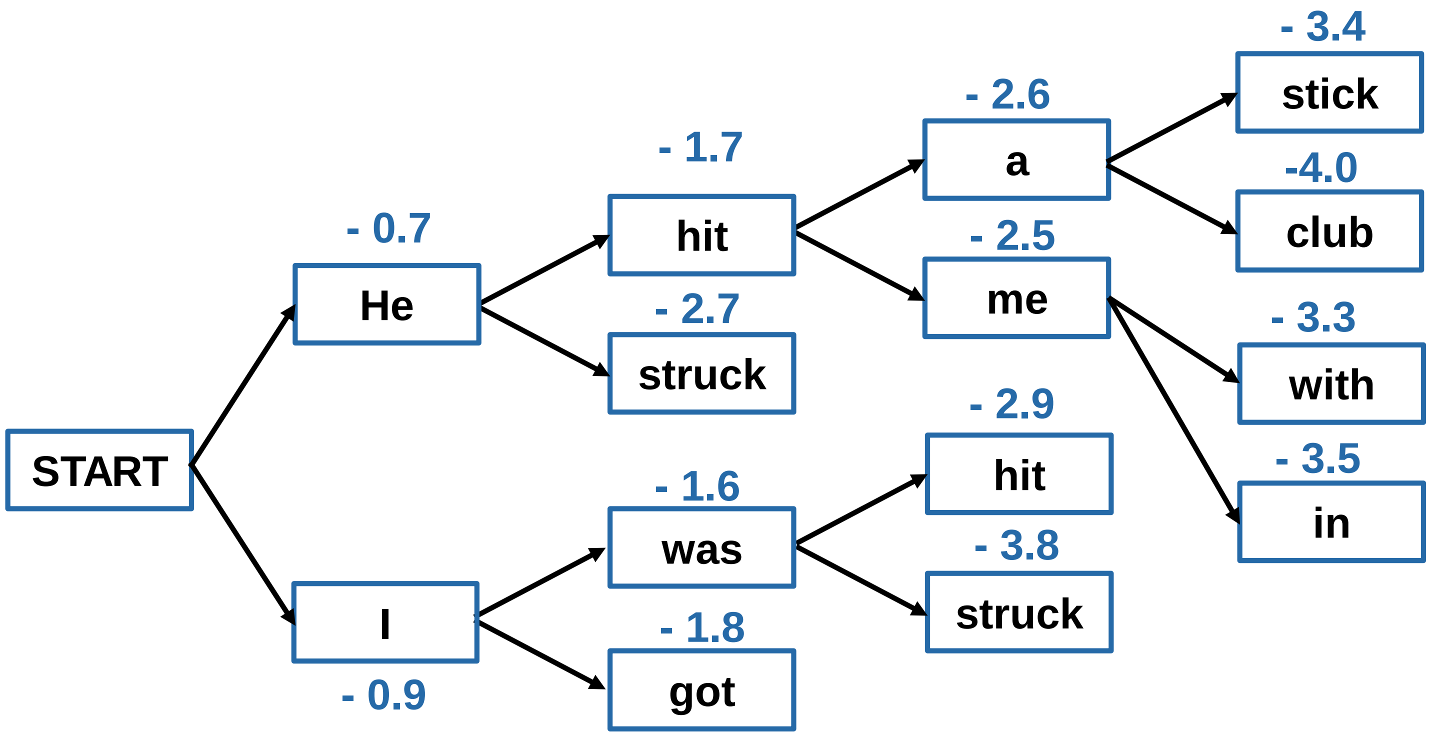

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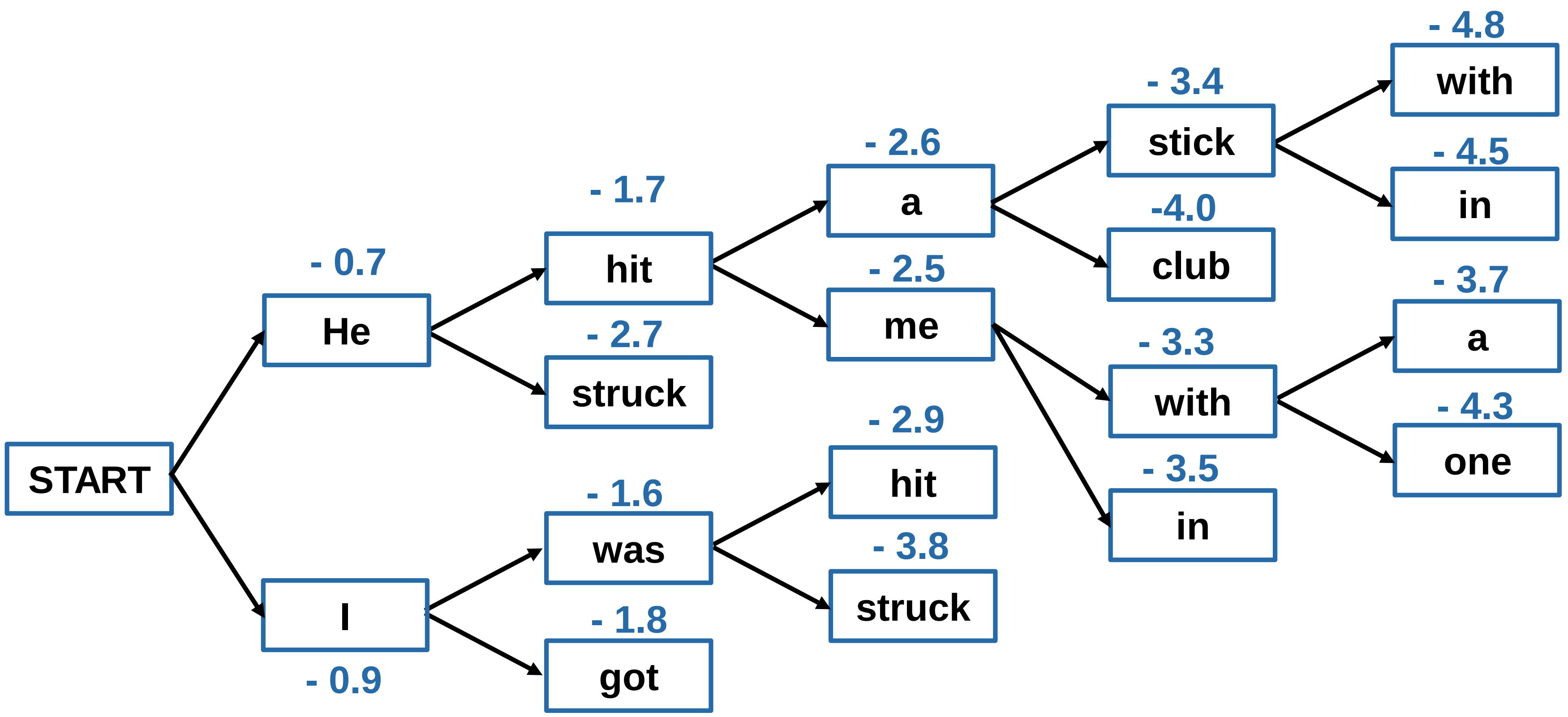

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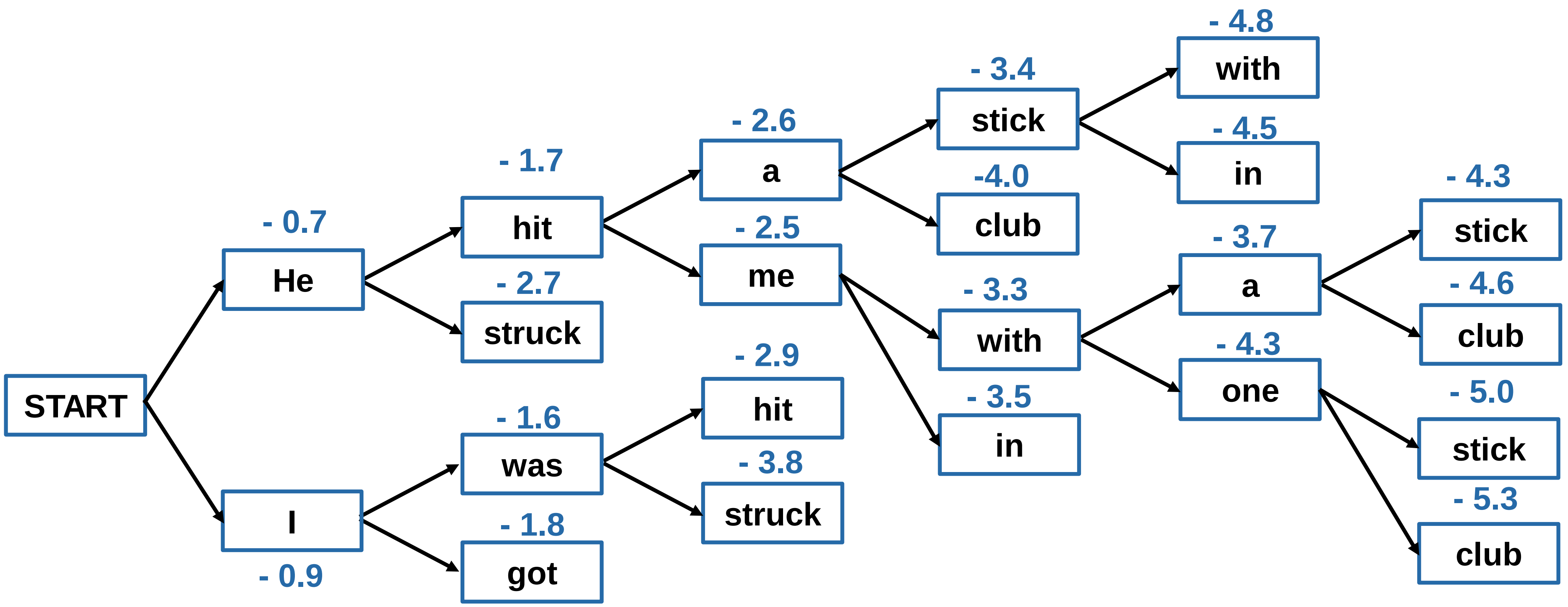

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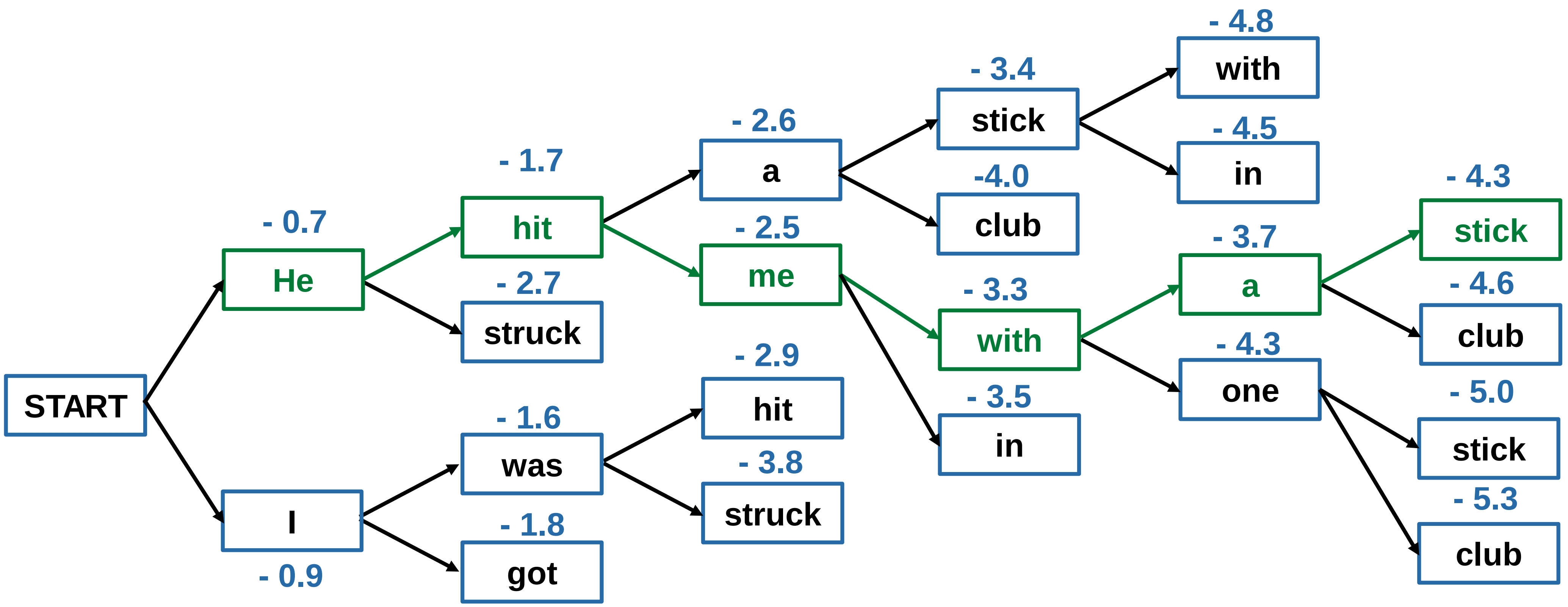

When to stop beam search and how to pick the most suitable hypothesis?

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    - N (predefined) number of hypotheses have been completed.
- Absolute hypotheses scores can be deceiving.

$$score(\hat{y}^{<1>}, \hat{y}^{<2>}, \dots, \hat{y}^{<t>}) = \sum_{i=0}^{t} \log P_{LM}\,(\hat{y}^{i} | \hat{y}^{<1>}, \hat{y}^{<2>}, \dots, \hat{y}^{<i-1>}, x)$$

  - Normalised scores are better estimates of suitability.

The NMT has some merits and demerits

- Provides better performance.
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- Less interpretable
  - Difficult to track errors
- Hard to exert control
  - Cannot specify rules
- Safety concerns
  - Model can say whatever it wants.

MT models are evaluated using BLEU metric

- It compares machine translation with one or more human translations and computes a similarity score based on n-gram precision and brevity penalty.
    - Checks how many n-grams generated by MT are actually present in human translation.

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- BLEU is useful but imperfect.

  - There can be many valid translations. It does not consider semantic similarity between words, or inclusion of all reference information in candidate.

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METEOR is another automatic evaluation metric for machine translation

- METEOR (Metric for Evaluation of Translation with Explicit ORdering) combines n-gram precision and recall.

$$MeteorScore = \frac{Prec \times Recall}{\alpha . Prec + (1-\alpha)\, Recall}\left(1 - \gamma\left(\frac{chunks}{u_m}\right)^{\beta}\right)$$

$chunks$ = bigram/trigram matches, u_m = unigrams in candidate
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Source: Auf der Matte saß die Katze

Candidate: On the mat sat the cat

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- Considers semantic similarity for matching.

- Correlates better with human judgement.

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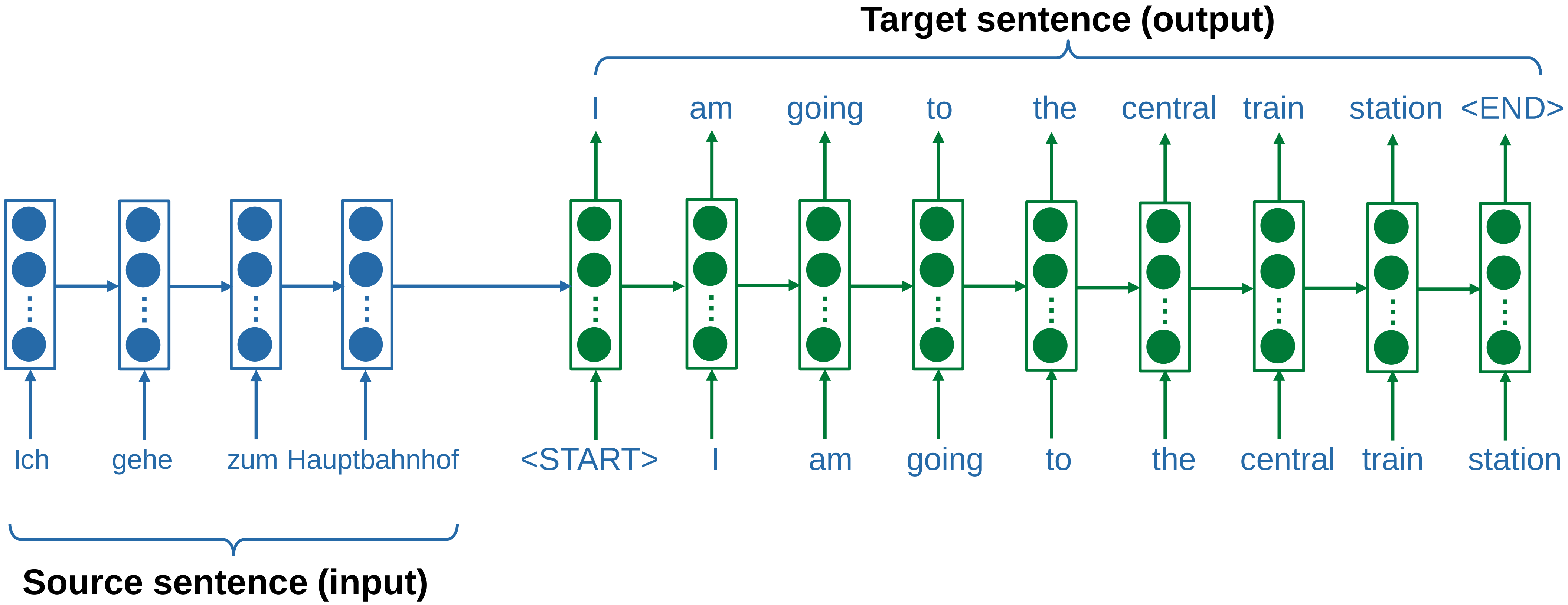
The problem of machine translation is far from solved

- Machine translation has achieved a lot but many challenges still remain.
  - Out of vocabulary words.
  - Domain mismatch.
  - Maintaining wider context.
  - Low-resource language pairs.

Interesting Read: *https://www.skynettoday.com/editorials/state_of_nmt*

Classical seq2seq model has a few shortcomings



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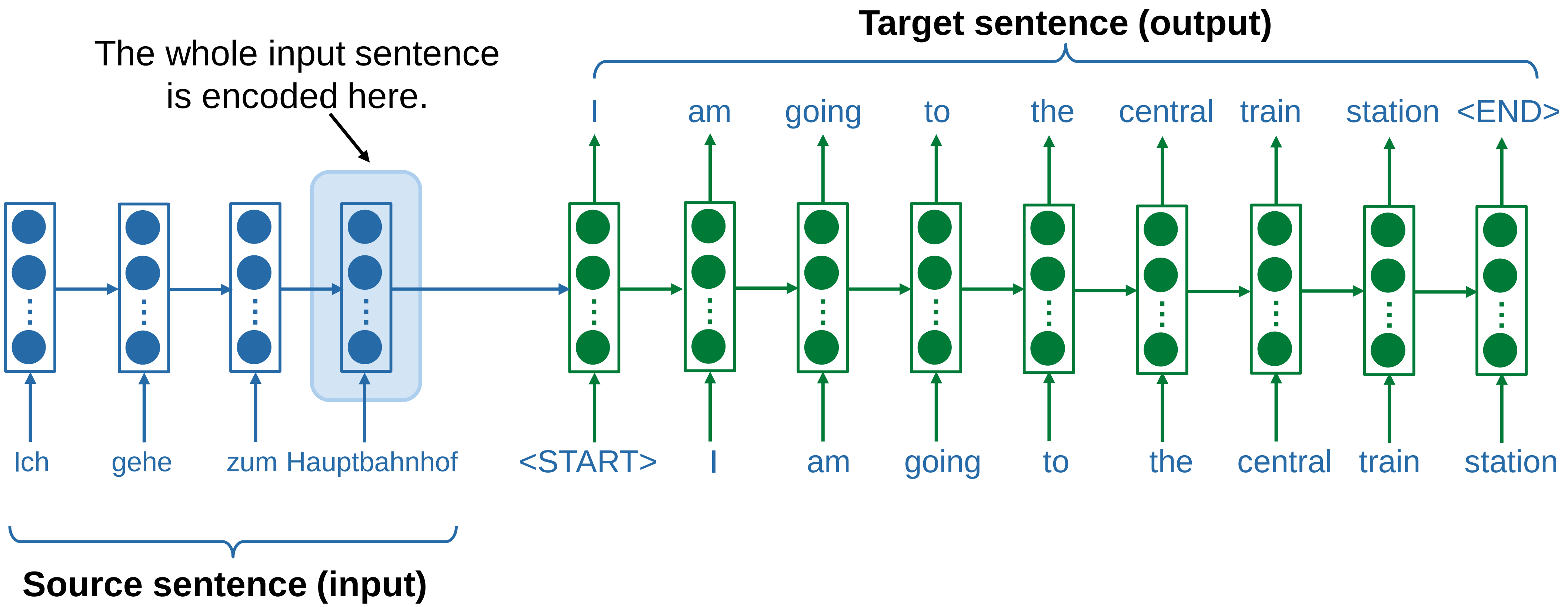

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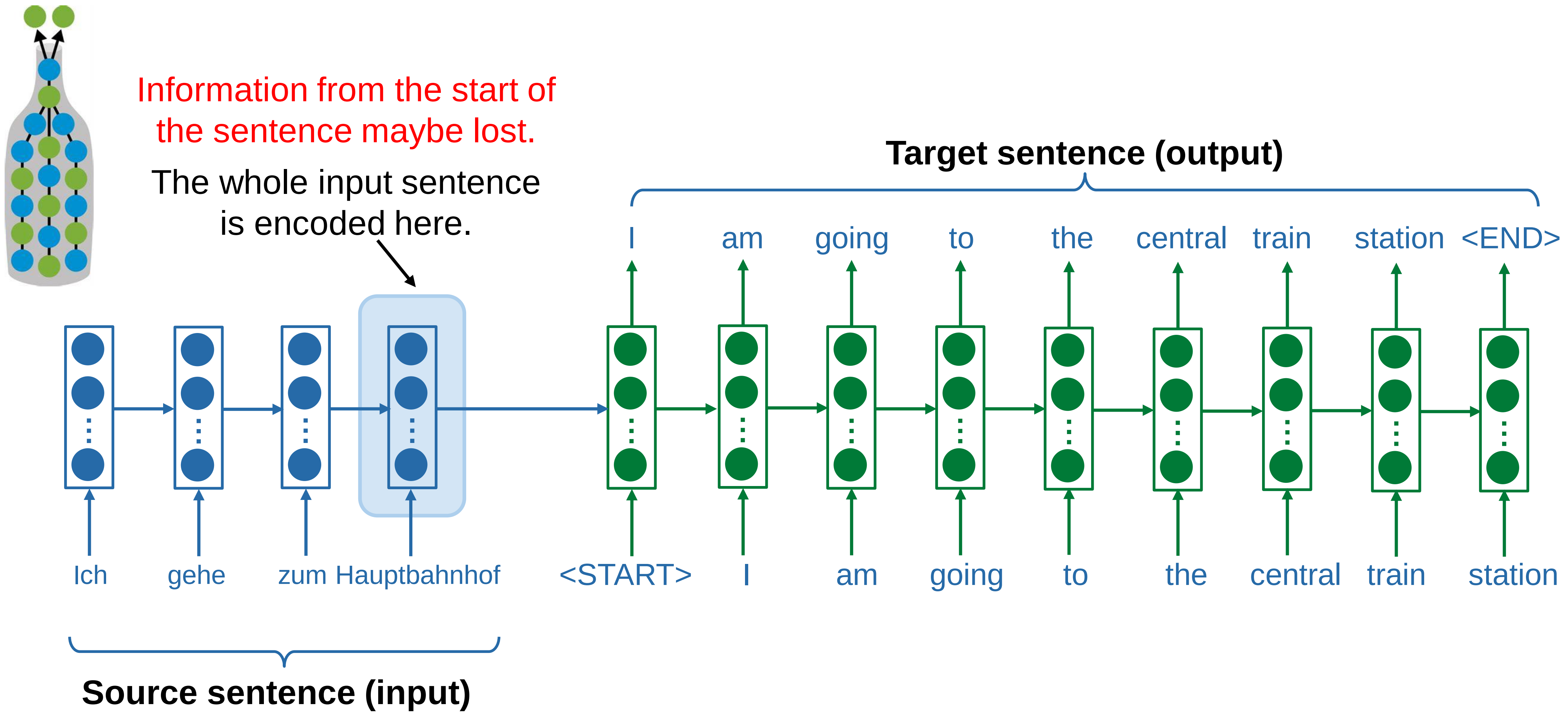

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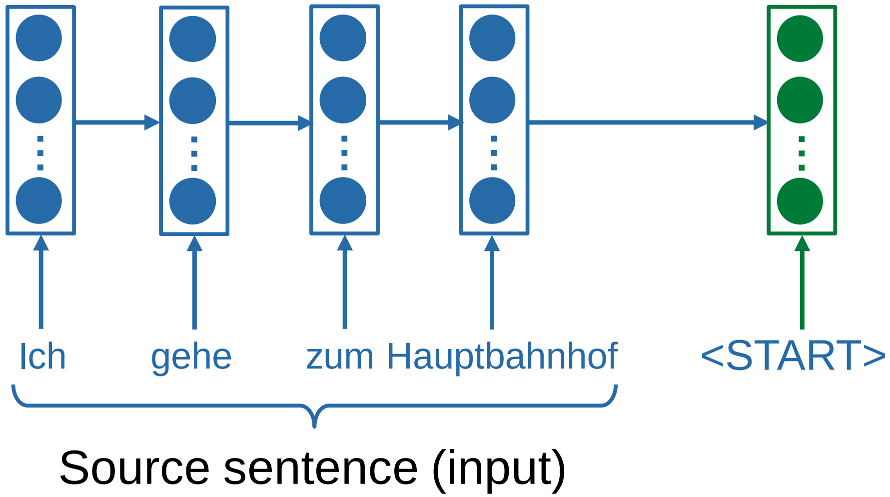
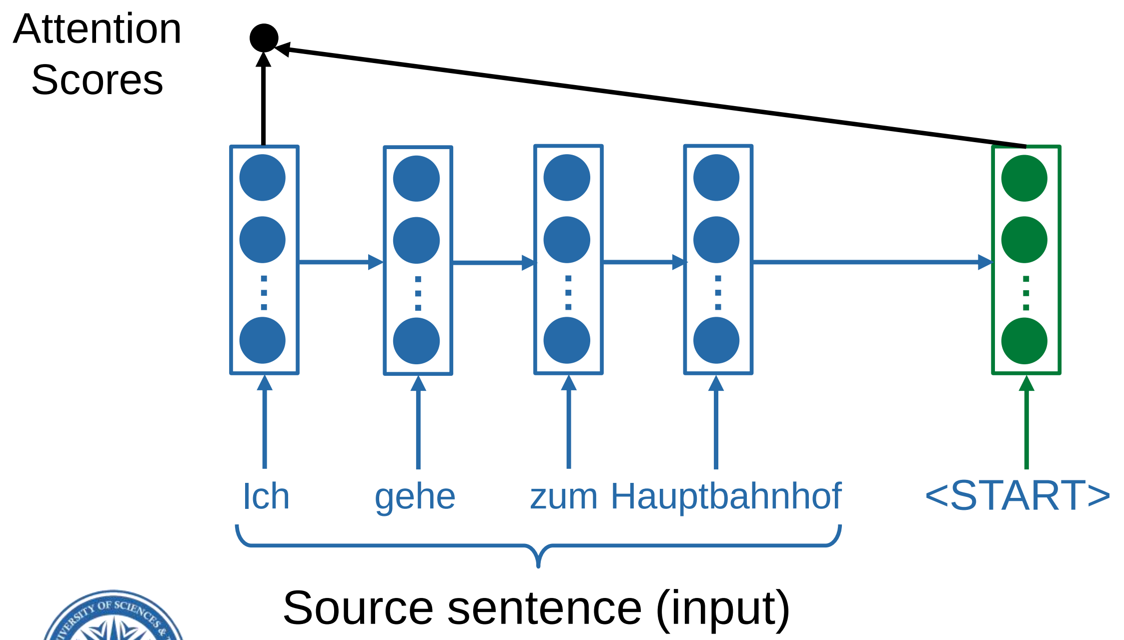


At each decoder time step t, take dot product of decoder activation $da^{<t>}$ and encoder activations $ea^{<1>}, ea^{<2>}, \ldots, ea^{<T_x>}$ to get attention scores.



Mathematically,

$$e_1^{<t>} = [\boldsymbol{da}^{<t>}]^T . \boldsymbol{ea}^{<1>}$$

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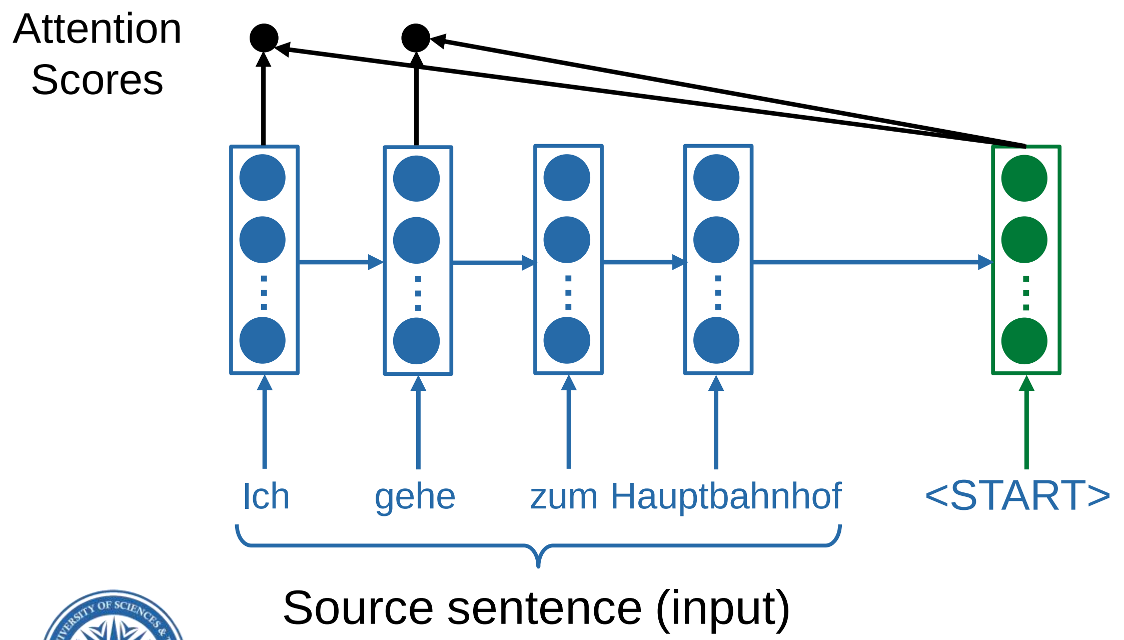

Mathematically,

$$e_2^{<t>} = [\boldsymbol{da}^{<t>}]^T . \boldsymbol{ea}^{<2>}$$

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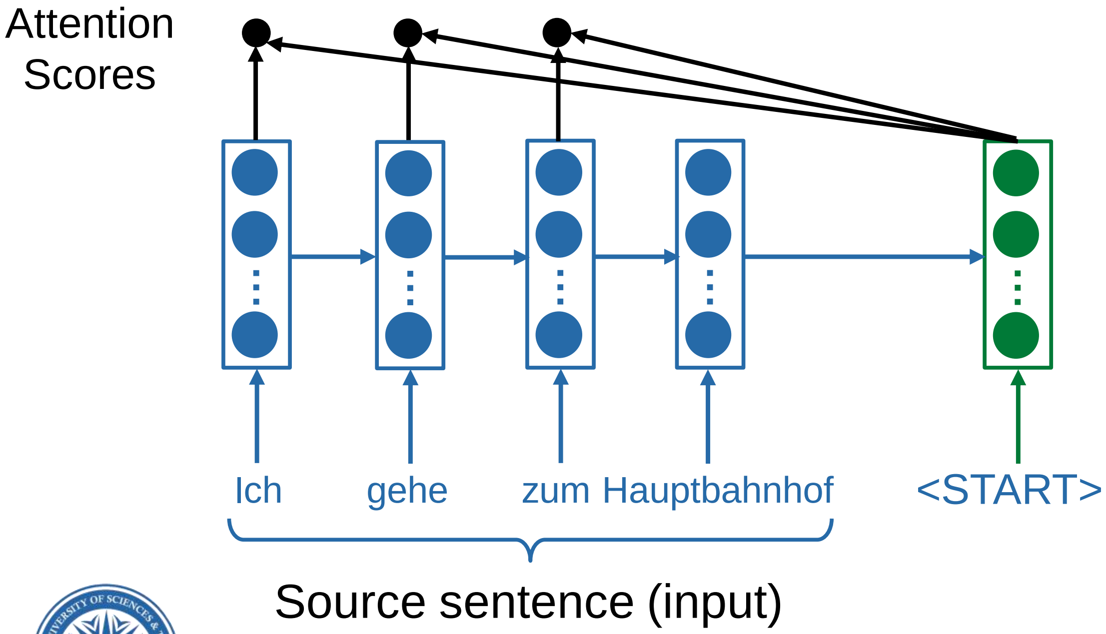

Mathematically,

$$e_3^{<t>} = [\boldsymbol{da}^{<t>}]^T . \boldsymbol{ea}^{<3>}$$

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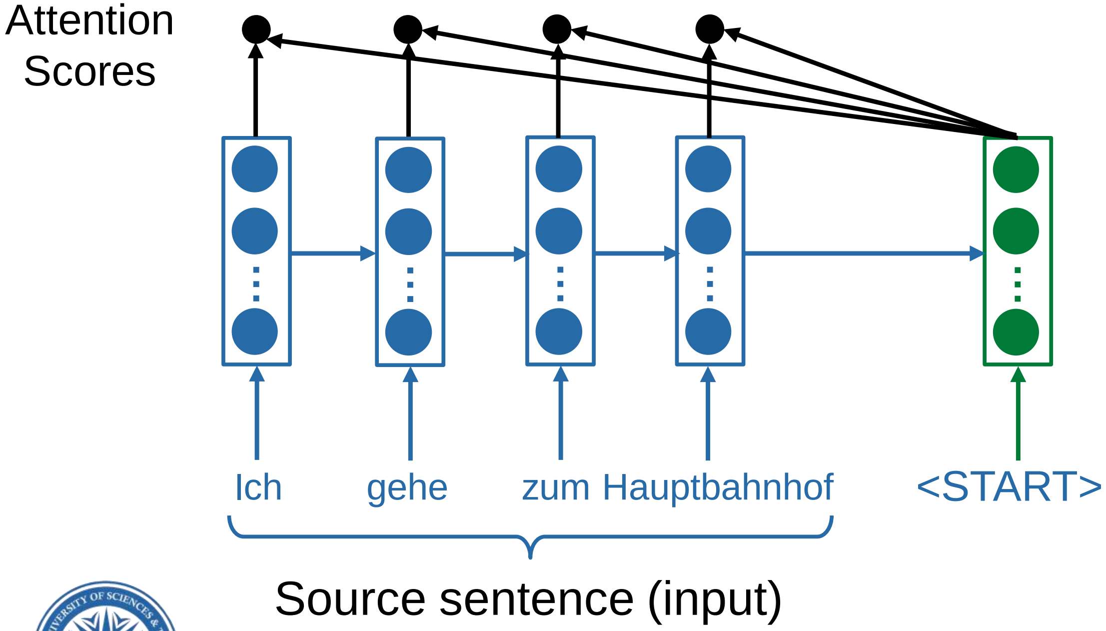


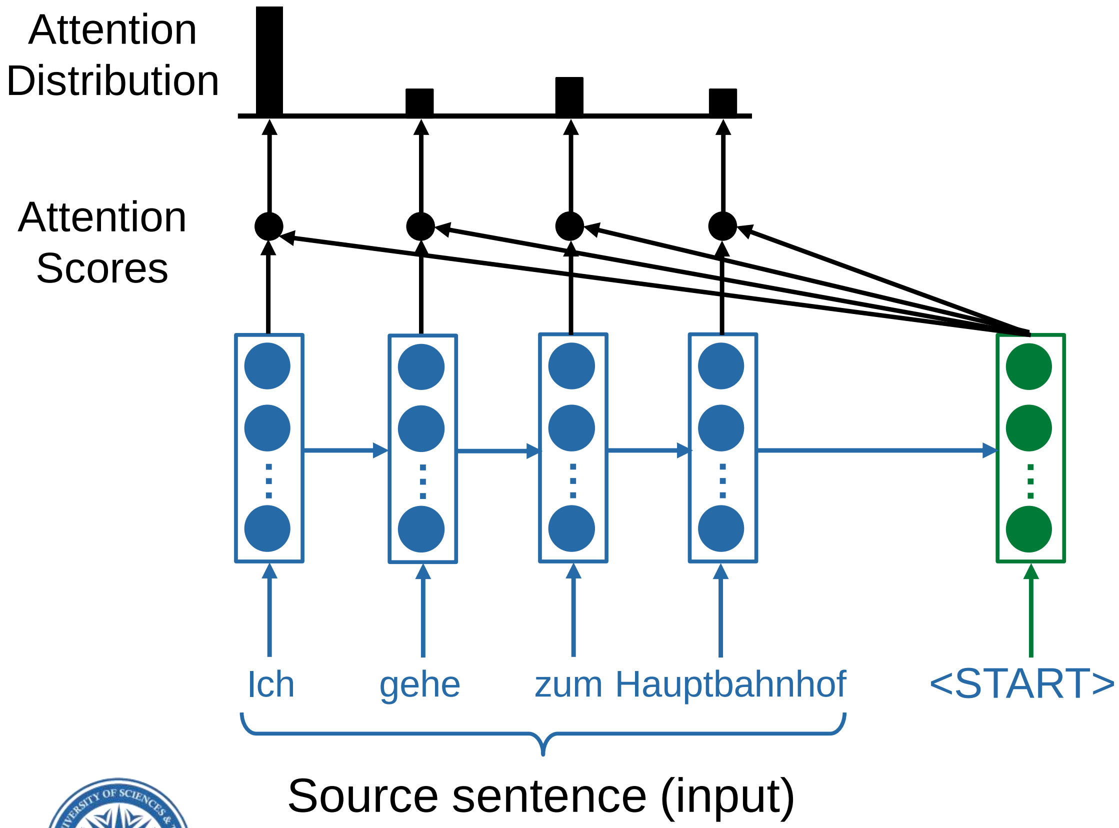
Mathematically,

$$e_4^{<t>} = [\boldsymbol{da}^{<t>}]^T . \boldsymbol{ea}^{<4>}$$

$$\boldsymbol{e}^t = [e_1^{<t>}, e_2^{<t>}, \ldots, e_{T_x}^{<t>}]$$

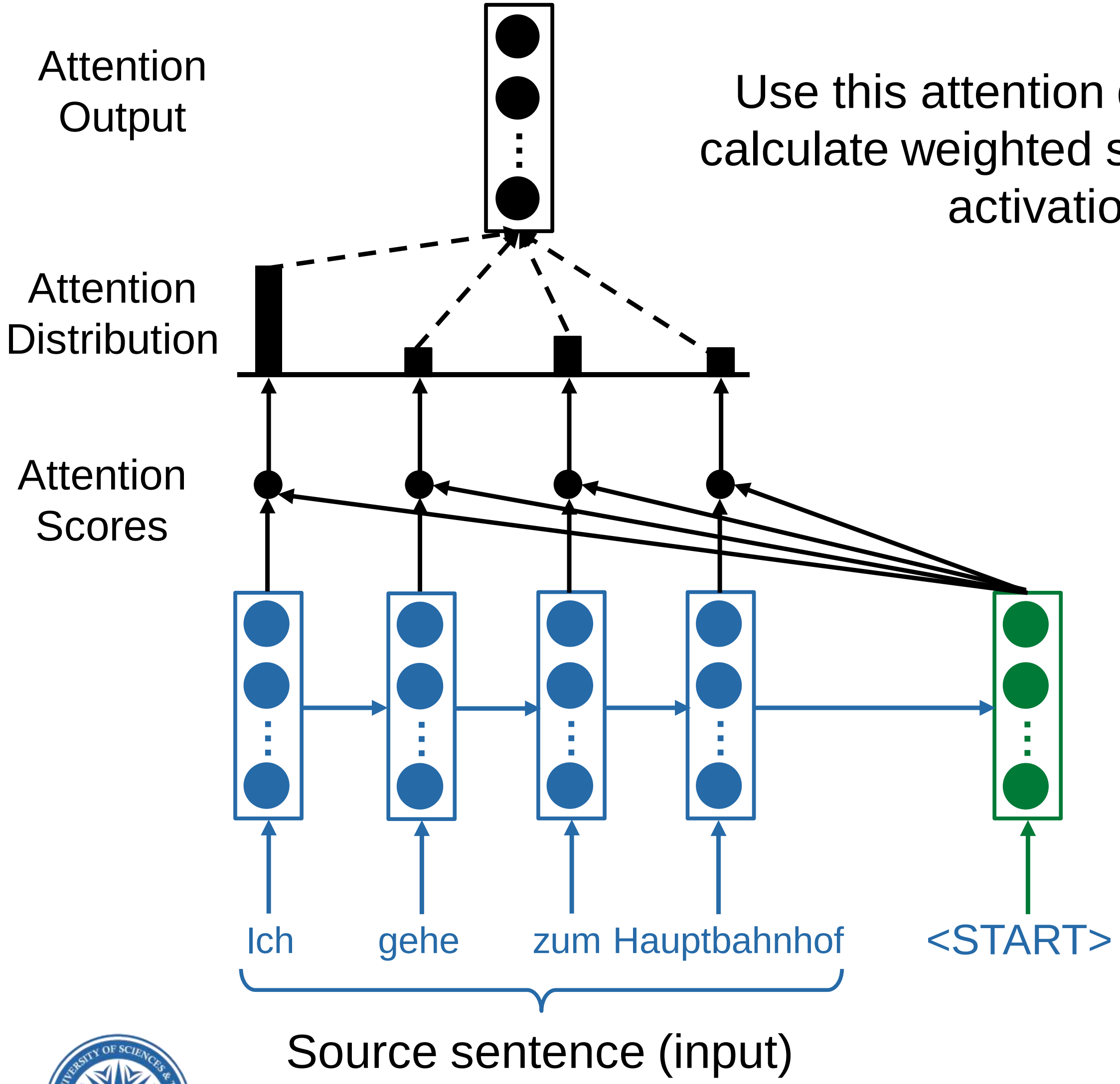
Information bottleneck in seq2sec models can be removed using Attention

Take $softmax$ of attention score to turn these values into probability distribution



Mathematically,

$$\boldsymbol{\alpha}^{<t>} = softmax\,(\boldsymbol{e}^{t})$$



Use this attention distribution to calculate weighted sum of encoder activations.

Mathematically,

$$\boldsymbol{a}^{<t>} = \sum_{i=1}^{T_x} \boldsymbol{\alpha}_i^{<t>} \boldsymbol{ea}^{<i>}$$

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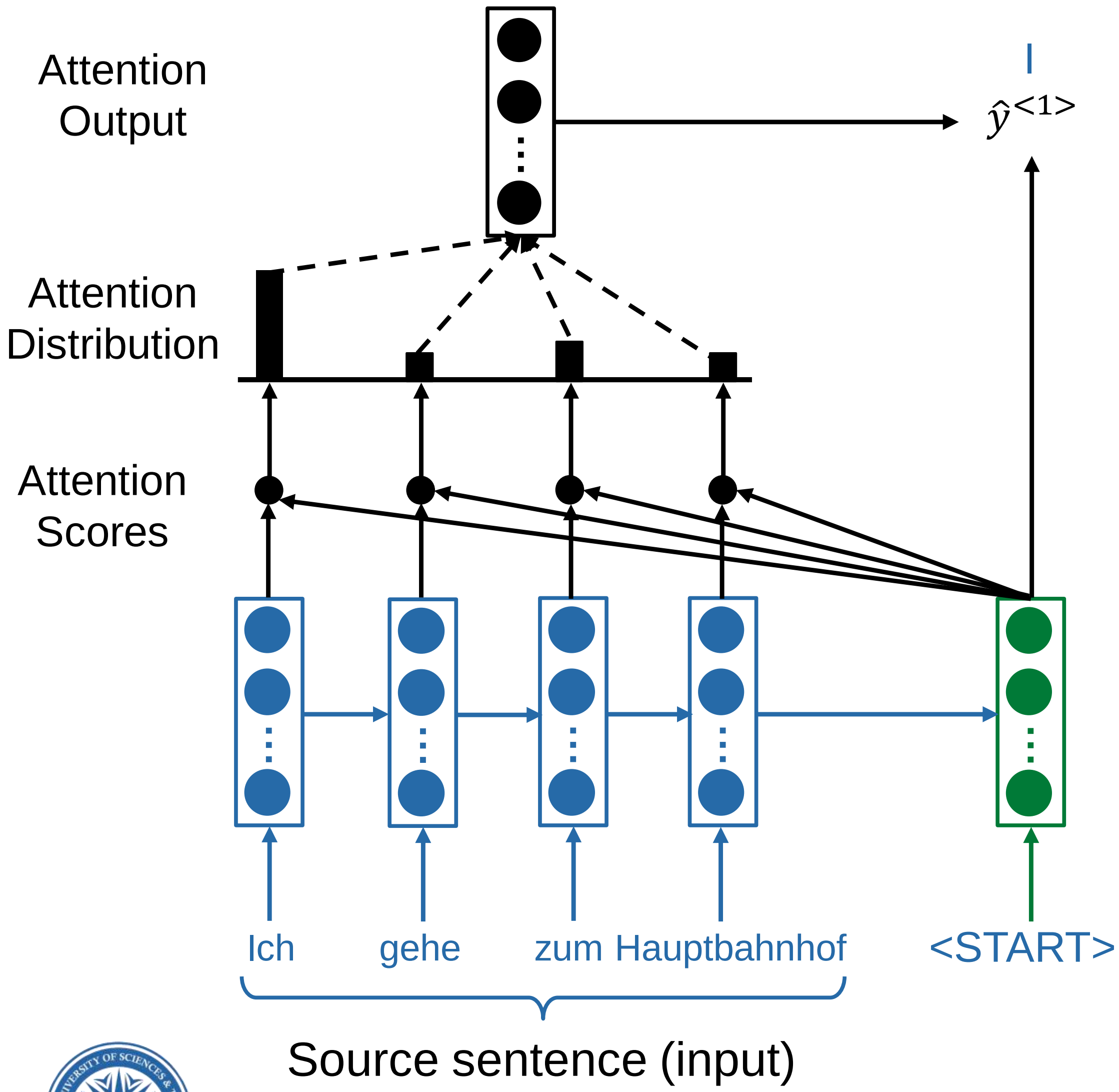

Attention output is used to influence the generation of word at this time step.

Concatenate attention output with decoder activation and calculate $\hat{y}^{<t>}$.

Mathematically,

$$\hat{y}^{<t>} = activation\ ([\boldsymbol{a}^{<t>} : \boldsymbol{da}^{<t>}])$$

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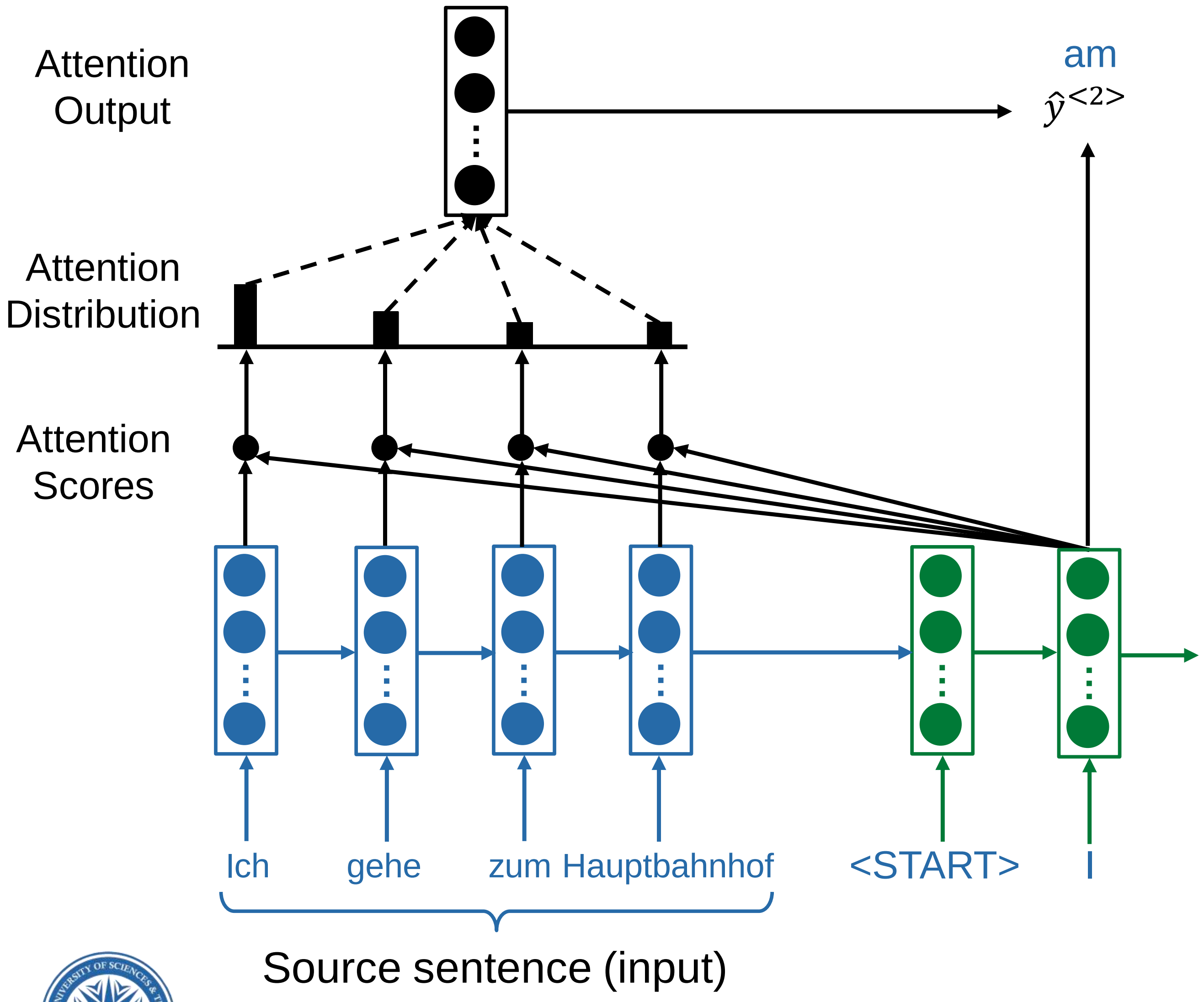

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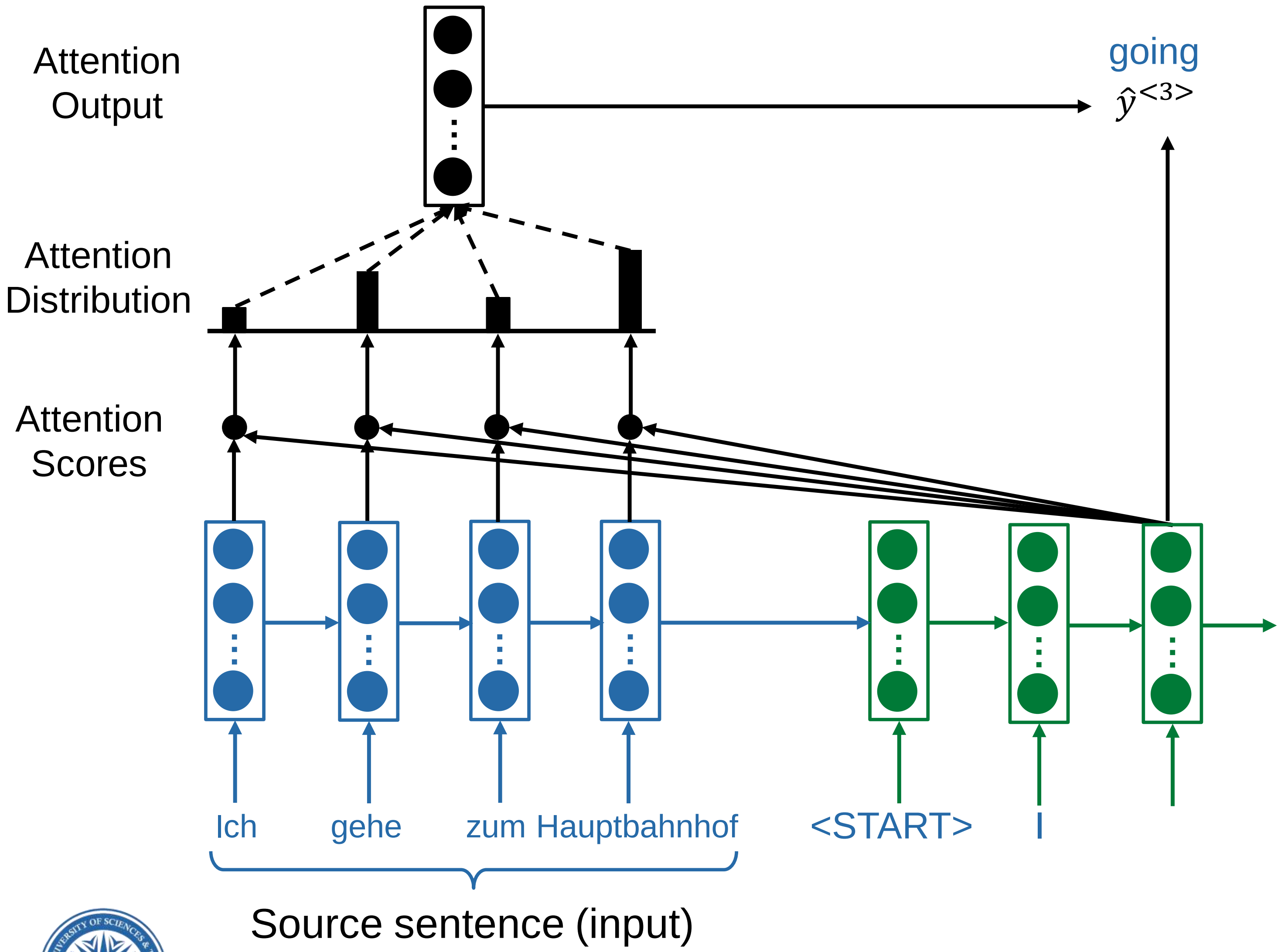

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- It also helps with vanishing gradient.
    - Direct connections between encoder and decoder are helpful especially in longer sentences.
- Attention may provide some interpretability.
    - Analysis of attention output can help understand what the decoder was fixating at while predicting a certain target word.
    - Soft alignment is achieved for free without even explicitly training for it.

Attention can be implemented in multiple ways

- To compute $\boldsymbol{e} \in \mathbb{R}^N$ from encoder activations $\boldsymbol{h_1}, \boldsymbol{h_2}, \dots, \boldsymbol{h_N} \in \mathbb{R}^{d_1}$ and decoder activations $\boldsymbol{s} \in \mathbb{R}^{d_2}$, we can use

  - Dot Product Attention.

$$e_i = \boldsymbol{s}^T \boldsymbol{h}_i \in \mathbb{R}$$

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  - Additive Attention.

$$e_i = \boldsymbol{v}^T \tanh(\boldsymbol{W}_1 \boldsymbol{h}_i + \boldsymbol{W}_2 \boldsymbol{s}) \in \mathbb{R}$$

  Here $\boldsymbol{W}_1 \in \mathbb{R}^{d_3 \times d_1}$ and $\boldsymbol{W}_2 \in \mathbb{R}^{d_3 \times d_2}$ are learnable weight metrices, $v \in \mathbb{R}^{d3}$ is a weight vector, and d_3 is a hyperparameter called attention dimensionality

Do you have any problem?

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