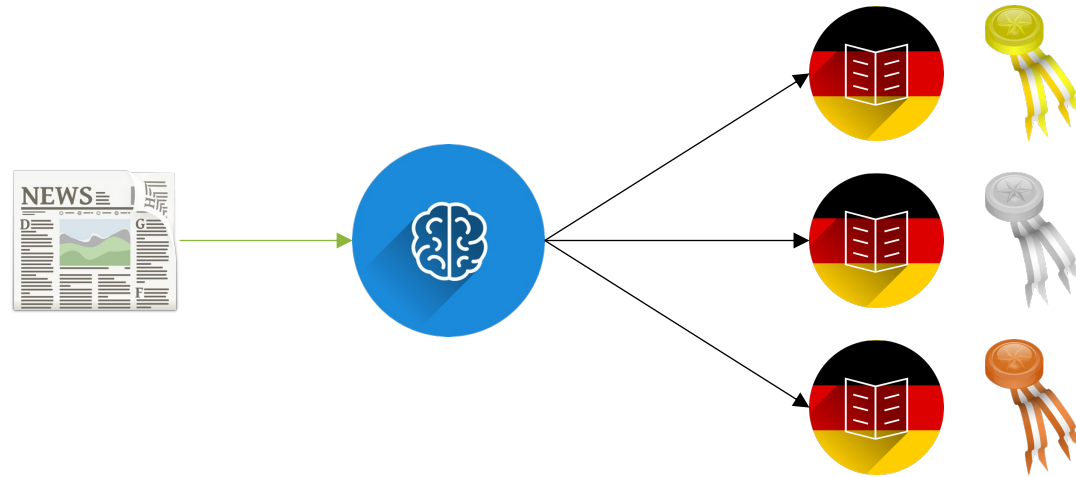


# 10 - Decoding

# Encoder – Decoder: Translation

- How do we generate the translation ?

# Machine Translation - Translation



- Search for possible translations
- Model assigns score to each translation
- Find most probable translation

# Overview

- Search Problem
- Search Algorithms
- Model/Search errors
- Modeling combination
  - Ensemble
  - Reranking

# Encoder – Decoder: Translation

- How do we generate the translation
  - Search for the most accurate translation:

$$y^* = \operatorname{argmin}_y E(y, \bar{y})$$

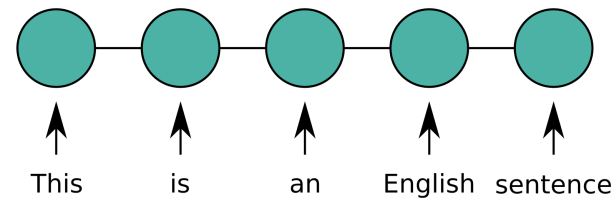
- At translation time, we don't have the reference  $\bar{y}$

- Search for the most probable translation:

$$y^* = \operatorname{argmax}_y P(y|x)$$

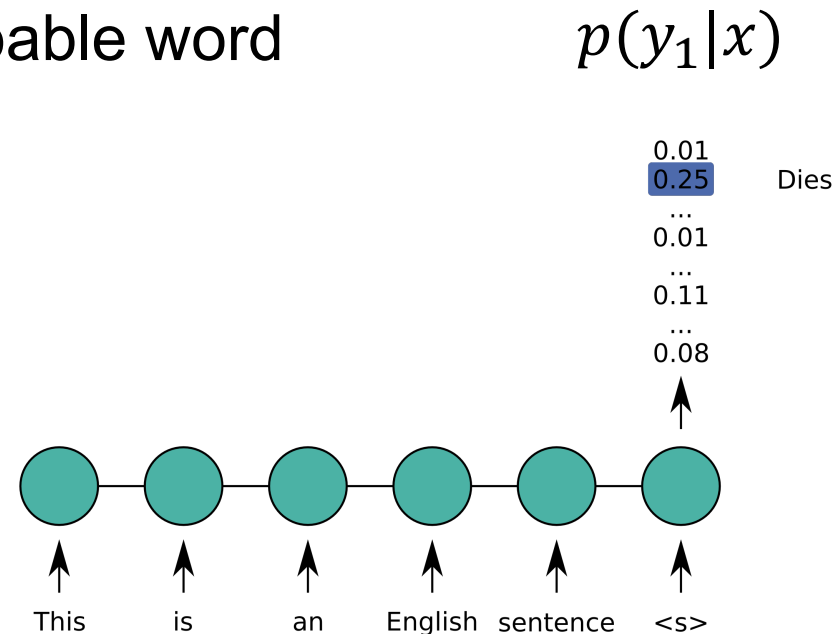
# Basic search

- Input source sentence
  - Forward pass



# Basic Search

- Input source sentence
  - Forward pass
- Input <s>
  - Calculate output probabilities
  - Select most probable word

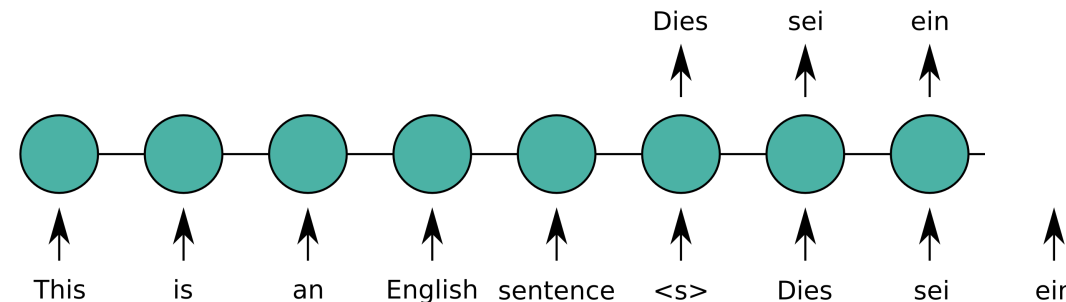


- able word
- get word
- $p(y_2|x, y_1)$
- 0.01  
0.05  
...  
**0.31** sei  
...  
0.23 ist  
...  
0.08
- Dies
- This is an English sentence <s> Dies



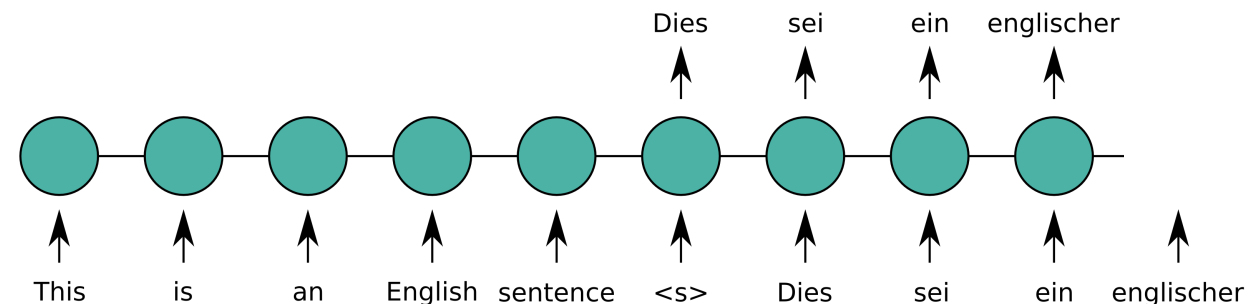
# Basic search

- Input source sentence
  - Forward pass
- Input <s>
  - Calculate output probabilities
  - Select most probable word
- Input selected target word
- Continue



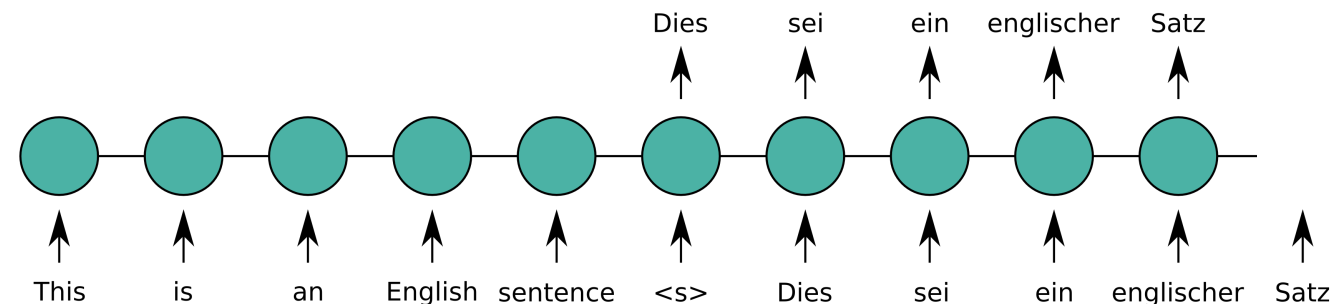
# Basic search

- Input source sentence
  - Forward pass
- Input <s>
  - Calculate output probabilities
  - Select most probable word
- Input selected target word
- Continue



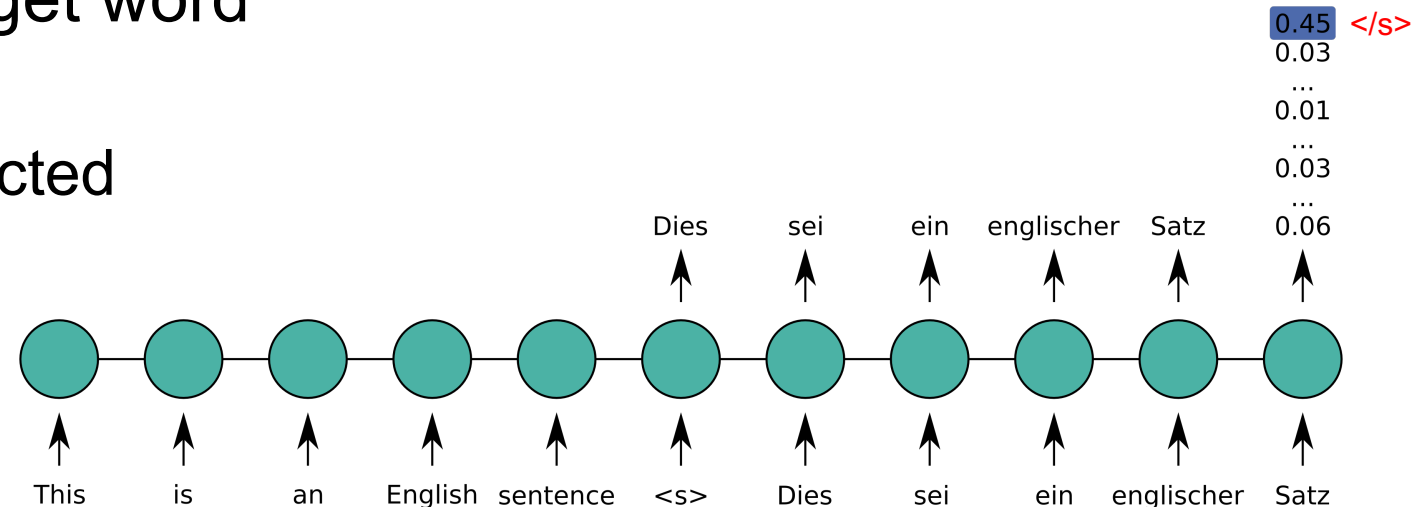
# Basic search

- Input source sentence
  - Forward pass
- Input <s>
  - Calculate output probabilities
  - Select most probable word
- Input selected target word
- Continue



# Basic search

- Input source sentence
  - Forward pass
- Input <s>
  - Calculate output probabilities
  - Select most probable word
- Input selected target word
- Continue
  - Until </s> is selected



# Search strategies

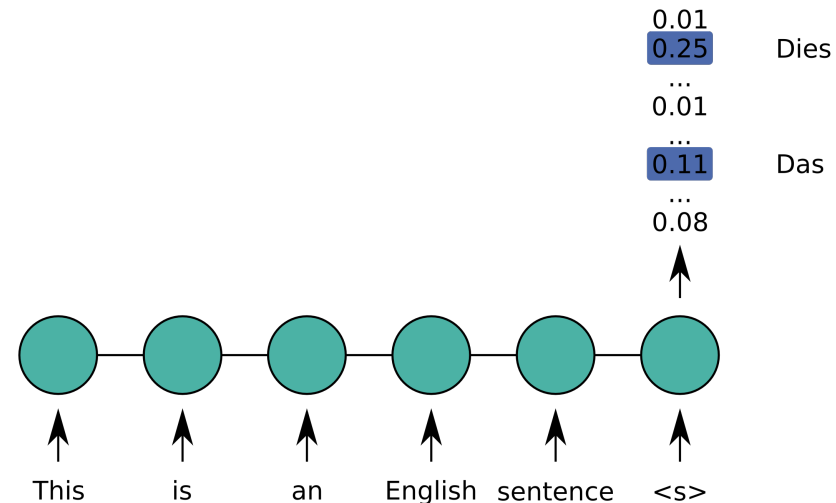
- Greedy search
  - Always select best target word
  - Problem:
    - Autoregressive model: Output influences input

# Greedy search - Challenge

■ First word:

$$p(y_1|x)$$

Hypothesis	
Dies	0.25
Das	0.11



# Greedy search - Challenge

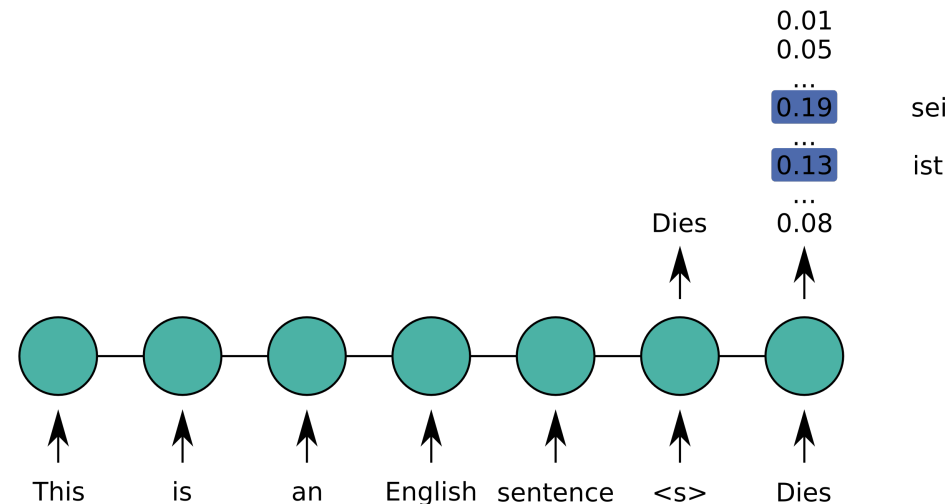
- First word:

$$p(y_1|x)$$

- Second word:

$$p(y_2|x, y_1)$$

Hypothesis	
Dies sei	0.0475
Dies ist	0.0325



# Greedy search - Challenge

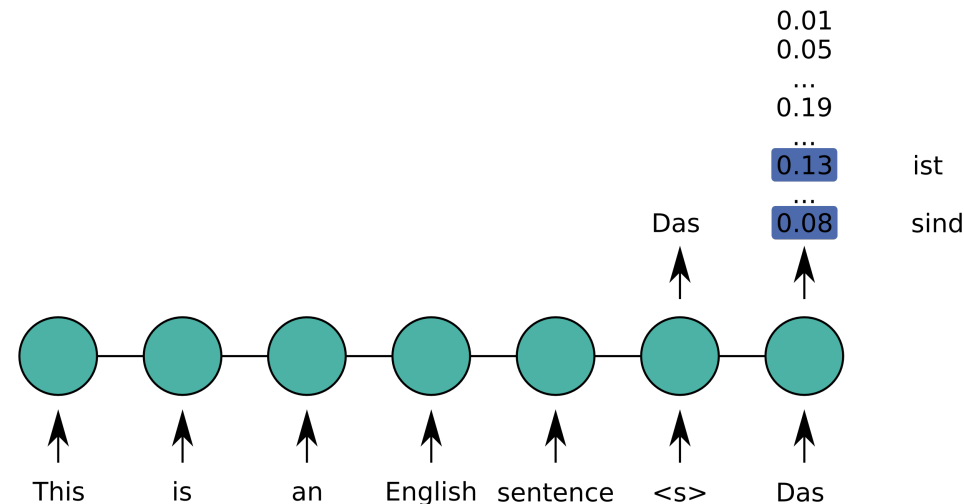
- First word:

$$p(y_1|x)$$

- Second word:

$$p(y_2|x, y_1)$$

Hypothesis	
Das ist	0.0539
Dies sei	0.0475
Dies ist	0.0325
Das sind	0.0187





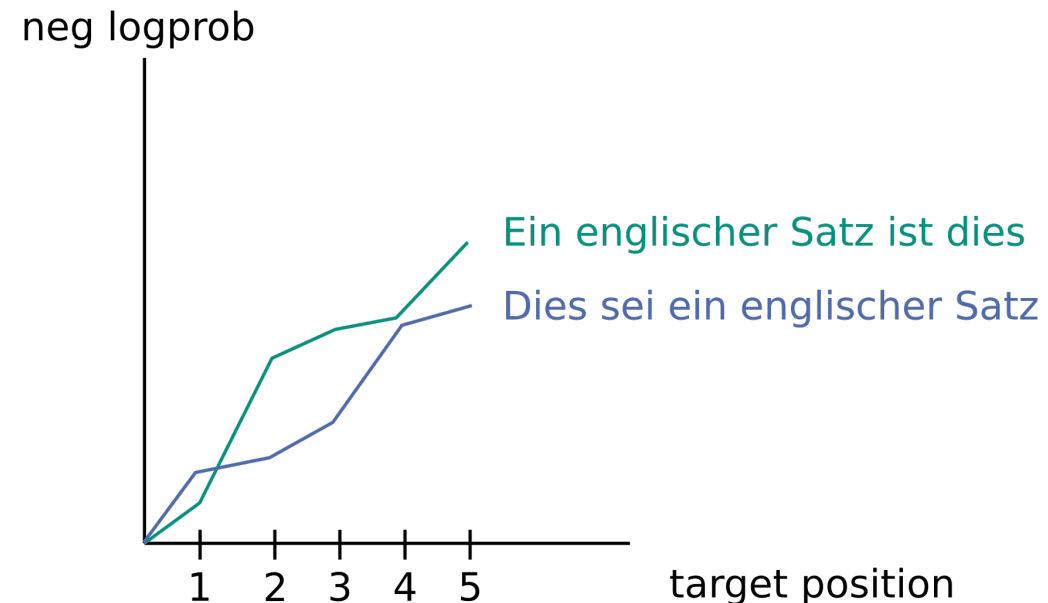
# Greedy search - Challenge

## ■ Greedy search

- Always select best target word
- Problem:
  - Might not find most probable sentence

## ■ Sentence probability:

$$p(e | f) = \prod_{j=1}^n p(e_j | f, e_1^{j-1})$$



# Search strategies

- Greedy search
- Exact search
  - Try all combinations

# Search strategies

- Greedy search
- Exact search
  - Try all combinations
  - Maximum a-posterior decoding
  - Challenge:
    - $|V_t|^{|y|}$  combinations
    - Only possible for very short sentences

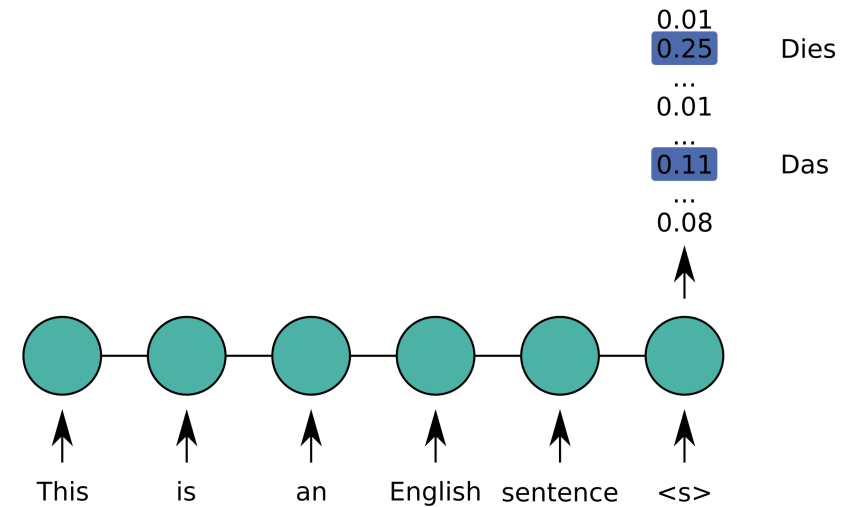
$$y^{\text{MAP}} = \arg \max_{h \in \mathcal{Y}} p_{Y|X}(h|x, \theta) .$$

# Search strategies

- Greedy search
- Exact search
- Sampling
  - Basic Idea: Randomly select next words based on conditional probability

# Sampling

- Randomly choose target word
  - Based on conditional probability
  - Draw uniform random number  $r$  between 0 and 1
  - Take word  $i$  with:
    - $\sum_{j=0}^{i-1} p(w_j|x, y) < r \leq \sum_{j=0}^i p(w_j|x, y)$
- Variation
  - Sample only from most probable  $k$  words



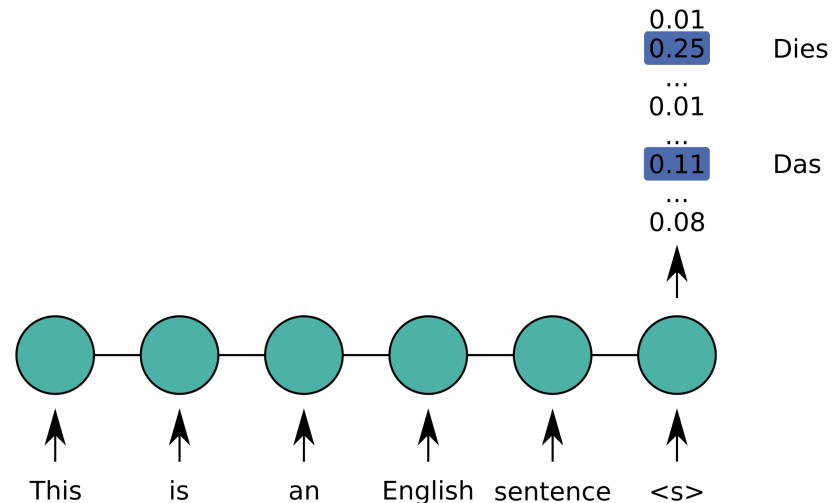
# Search strategies

- Greedy search
- Exact search
- Sampling
- Beam Search
  - Basic Idea: Keep the best  $n$  hypotheses
  - In NMT: Only small beam needed

# Beam search

- Beam Search:
  - Calculate output probabilities
  - Select best n translations

Hypothesis	
Dies	0.25
Das	0.11

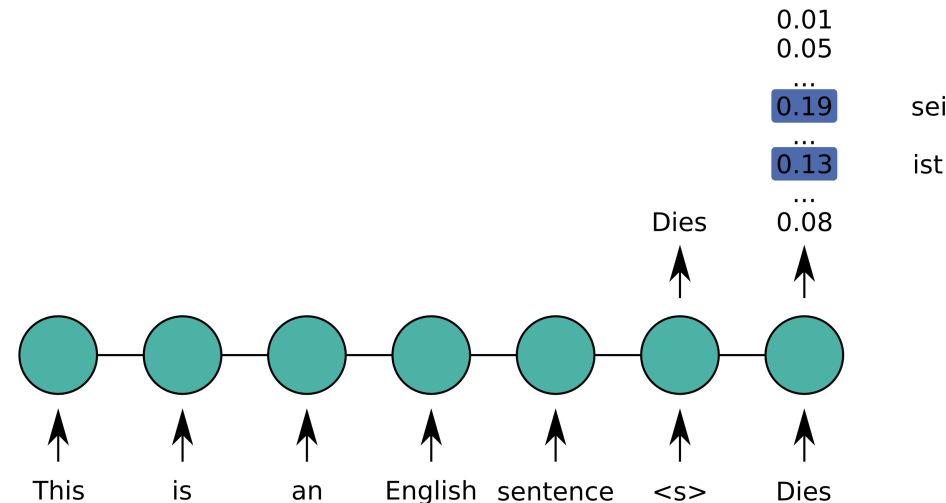


# Beam search

## ■ Beam Search:

- Calculate output probabilities
- Select best n translations
- Extend all hypothesis in beam

Hypothesis	
Dies sei	0.0475
Dies ist	0.0325

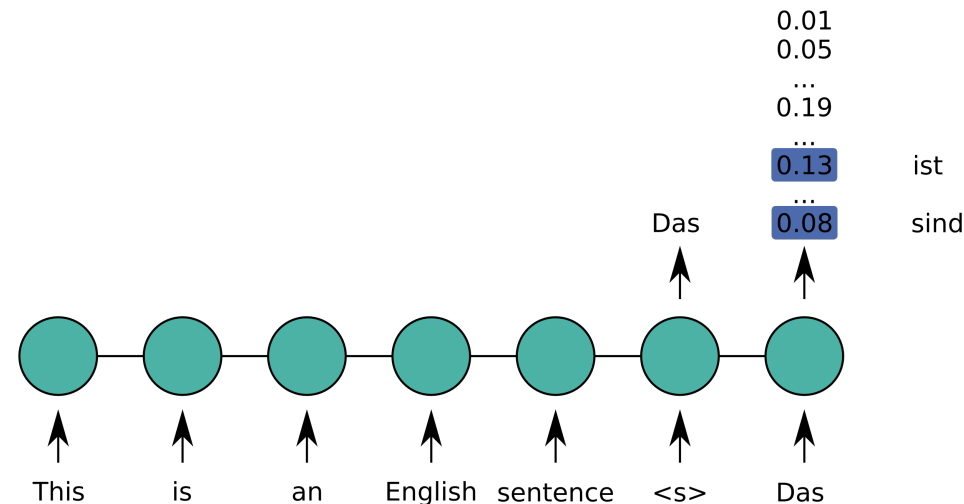




# Beam search

- Beam Search:
  - Calculate output probabilities
  - Select best n translations
  - Extend all hypothesis in beam

Hypothesis	
Das ist	0.0539
Dies sei	0.0475
Dies ist	0.0325
Das sind	0.0187

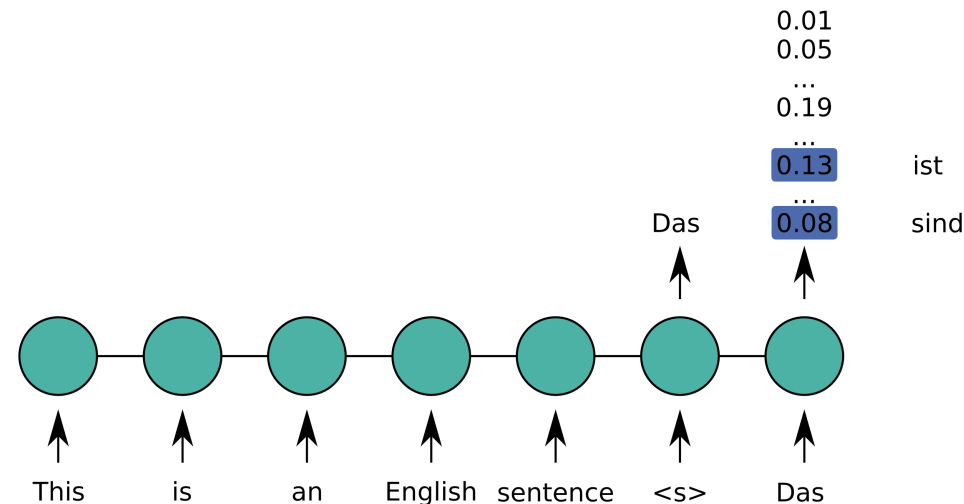


# Beam search

## ■ Beam Search:

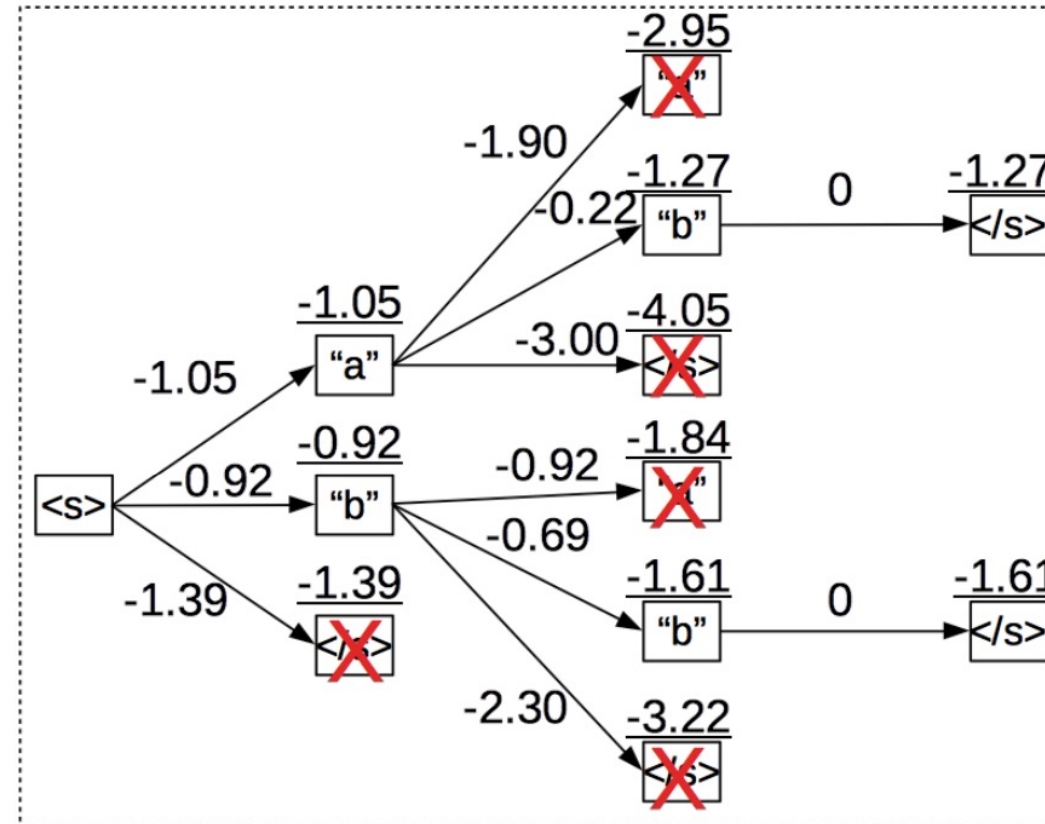
- Calculate output probabilities
- Select best n translations
- Extend all hypothesis in beam
- Prune hypothesis not in beam

Hypothesis	
Das ist	0.0539
Dies sei	0.0475



# Beam search

## ■ Beam Search:



(from Neubig 2019)

# Beam search

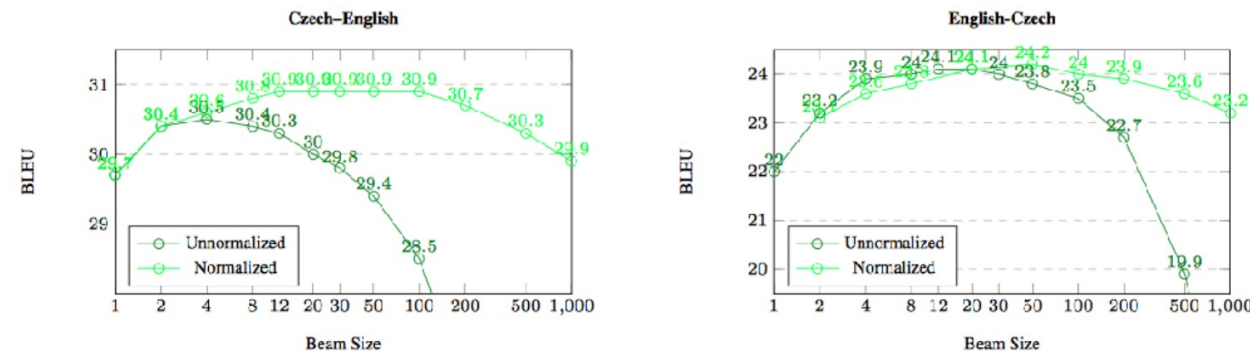
## ■ Beam Search:

### ■ SMT:

- Larger beam => larger search space => better score
- Trade-off between quality and speed (n=300)

### ■ NMT:

- Larger beam than an optimal number => more confusions
- Beyond that optimal beam size (5-12), quality decreases
- (Niehues et al., 2017):  $n < 50$  is sufficient, focus on modeling



(from Koehn and Knowles 2017)

# Search

- Model error:

- The model does not assign the highest probability to the correct translation

- Search error:

- The search does not find the translation with the highest probability

# Label / Length bias

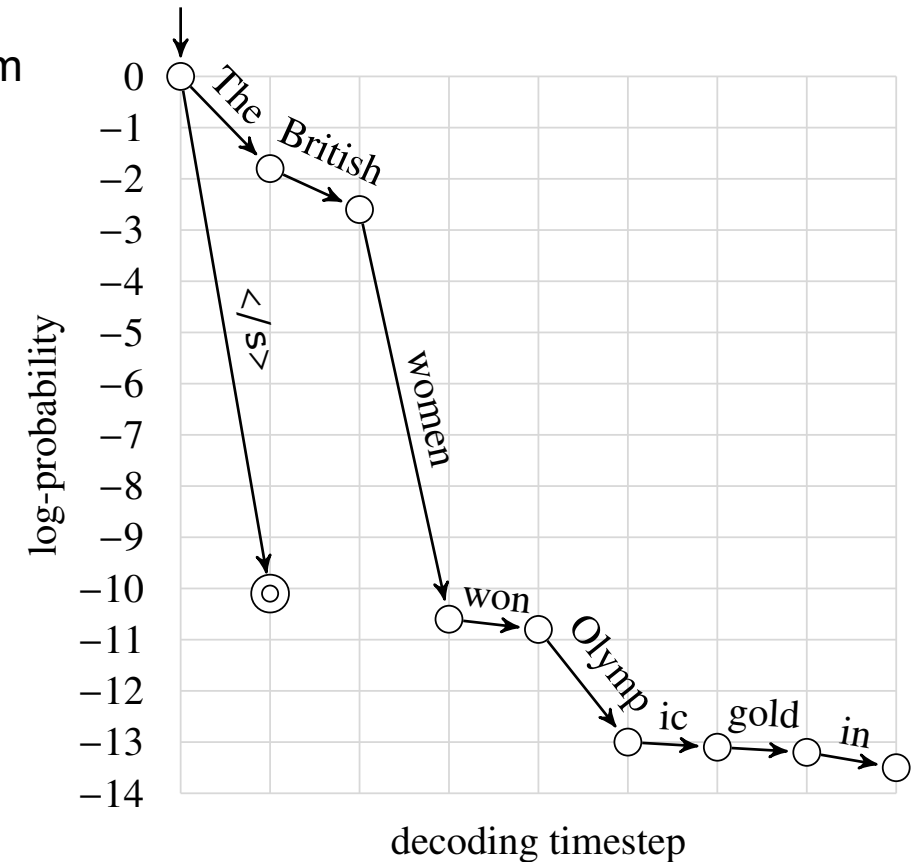
- Over-estimate probability of a prefix  $y_1, \dots, y_m$

- Multiply with conditional probabilities

$$p(y_{m+1} | x, y_1, \dots, y_m)$$

- No possibility to recover

- Prefer short translation



Murray and Chiang, 2018

# Label / Length bias

- Over-estimate probability of a prefix  $y_1, \dots, y_m$

- Multiply with conditional probabilities

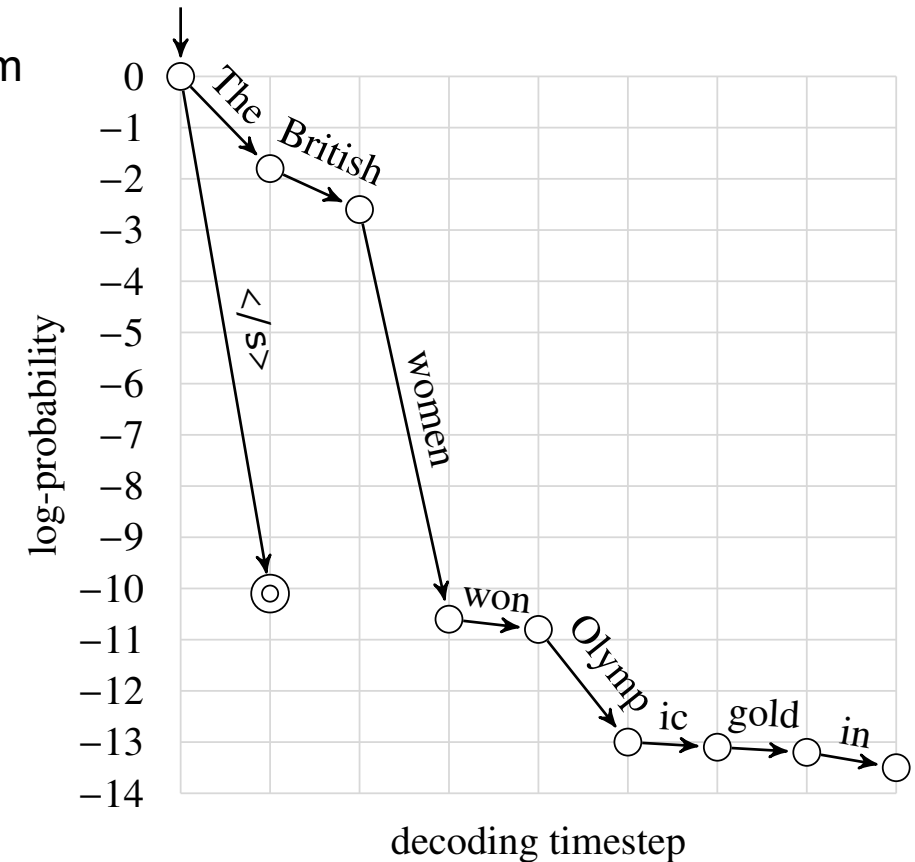
$$p(y_{m+1} | x, y_1, \dots, y_m)$$

- No possibility to recover

- Prefer short translation

- Model error

- Search error in greedy/beam search with small beam does prevent



Murray and Chiang, 2018

# Modeling sentence length

## ■ Length normalization

$$s'(e) = s(e) / m.$$

$$s'(e) = s(e) \left/ \frac{(5 + m)^\alpha}{(5 + 1)^\alpha} \right.$$

## ■ Word reward

$$s'(e) = s(e) + \gamma m.$$



# Search strategies

- Greedy search
- Exact search
- Sampling
- Beam Search
- Minimum Bayes Risk Decoding
  - Basic Idea:
    - Probability mass distributed over many good translations
    - Find a good representative

# Minimum Bayes Risk decoding

- Several good translation distributed according to  $P_{\text{human}}$
- $u(h, r)$ 
  - Utility of the hypothesis according to reference  $r$
- Idea:
  - Find translation with highest expected utility

$$\begin{aligned} h^{\text{best}} &= \arg \max_{h \in \mathcal{H}} \mathbb{E}_{r \sim P_{\text{human}}(\cdot|x)} \{u(h, r)\} \quad (1) \\ &= \arg \max_{h \in \mathcal{H}} \sum_{r \in \Omega} u(h, r) P_{\text{human}}(r|x). \end{aligned}$$

# Minimum Bayes Risk decoding

- Challenge:

- Reference translations unknown

- Idea:

- Rely on model

$$h^{\text{model}} = \arg \max_{h \in \mathcal{H}} \sum_{y \in \Omega} u(h, y) P_{\text{model}}(y|x)$$

# Minimum Bayes Risk decoding

- Challenge:
  - Sum over all hypothesis
- Idea:
  - Rely on finit sample
- Candidate pool  $H$
- Pseudo-references  $H_{\text{model}}$ 
  - Use same pool

$$h^{\text{MBR}} = \arg \max_{h \in \mathcal{H}} \frac{1}{|\mathcal{H}_{\text{model}}|} \sum_{y \in \mathcal{H}_{\text{model}}} u(h, y).$$

# Minimum Bayes Risk decoding

- Sampling:
  - Independent sampling
    - Uniform probability distribution on the set

$$h^{\text{MBR}} = \arg \max_{h \in \mathcal{H}} \frac{1}{|\mathcal{H}_{\text{model}}|} \sum_{y \in \mathcal{H}_{\text{model}}} u(h, y).$$

# Minimum Bayes Risk decoding

- Utility function:

- Compare hypothesis and pseudo-reference

- Related to automatic evaluation

- Examples:

- Sentence-level BLEU

- Neural Evaluation metrics

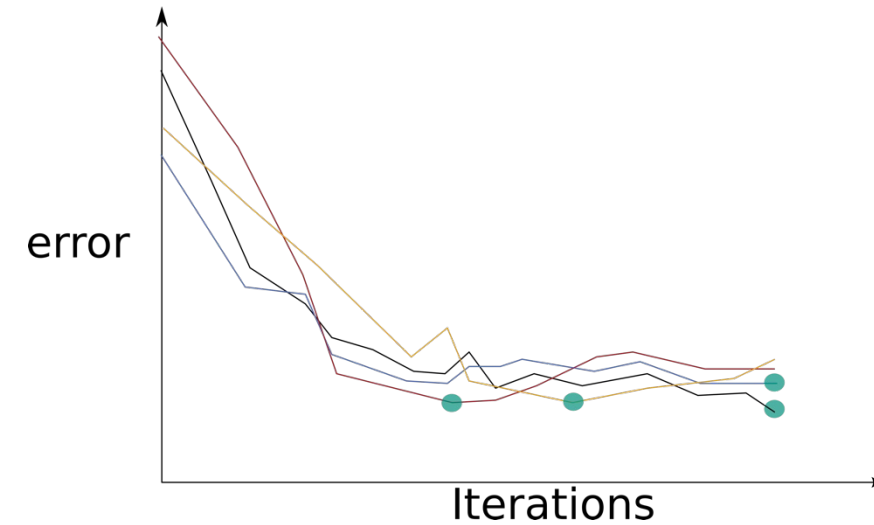
$$h^{\text{MBR}} = \arg \max_{h \in \mathcal{H}} \frac{1}{|\mathcal{H}_{\text{model}}|} \sum_{y \in \mathcal{H}_{\text{model}}} u(h, y).$$

# Combination of NMT models

- Randomly initialize models
  - Easy to create many different models
- Design decisions lead to different models
- Each model has strengths and weaknesses
- Methods:
  - Ensemble
  - Reranking

# Model Ensemble

- Combine different models
  - E.g. different initialization

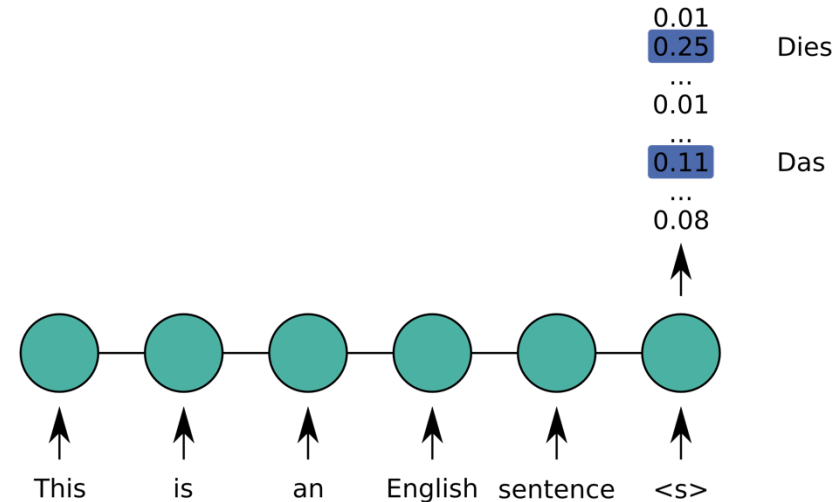




# Model Ensemble

- Combine different models
  - E.g. different initialization
- Combine output layer of different models
- Word probability:




$$P(e_i = j | e_1^{i-1}, F) = \frac{o_j}{\sum_{i=1}^N o_i}$$



# Ensemble

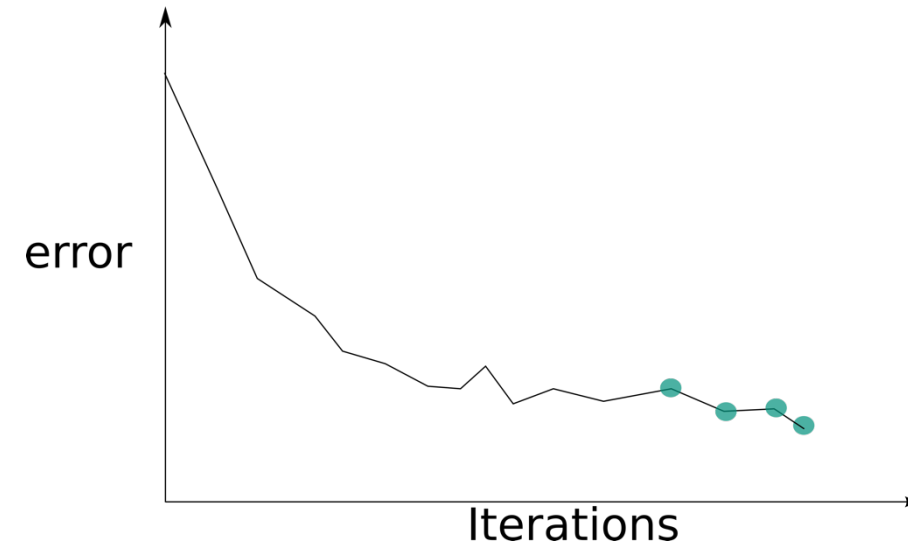
- Combine different models
  - E.g. different initialization
- Combine output layer of different models
- Word probability:

$$P(e_i = j | e_1^{i-1}, F) = \frac{\sum_{k=1}^K o_j^k}{\sum_{i=1}^N \sum_{k=1}^K o_i^k}$$

- Performance 
- Training speed 
- Decoding speed 

# Check-point ensemble

- Train one model
  - Save checkpoints



# Check-point ensemble

- Train one model
  - Save checkpoints
- Ensemble models from different checkpoints

- Performance
- Training speed
- Decoding speed



# Rescoring/Reranking

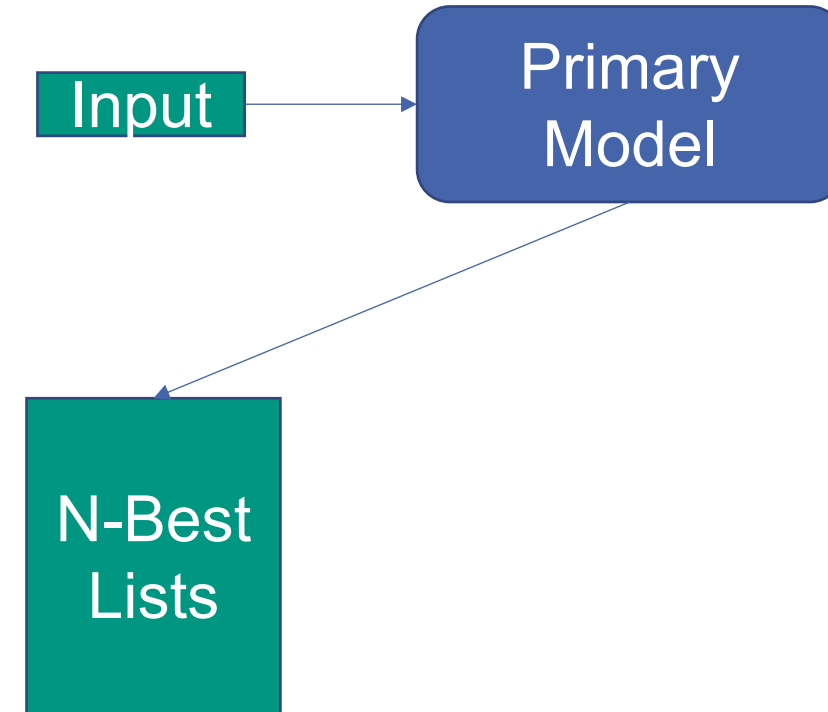
- Other ways of modeling translation probability might be complementary
- Different word representations
  - Byte-pair encoding, Character, ...
- Right to left decoding:
  - I go home  $\rightarrow$  . home go I
- Inverse translation directions
  - $P(\text{I gehe nach Hause} \mid \text{I go home})$
  - $P(\text{I go home} \mid \text{I gehe nach Hause})$

# Rescoring/Reranking

- Other ways of modeling translation probability might be complementary
- Challenge:
  - Different search space
  - Cannot score same partial hypothesis
  - $P(\text{I go home} \mid \text{I ???????})$
- Idea:
  - Create finite sample of search space
  - Score only finite sample

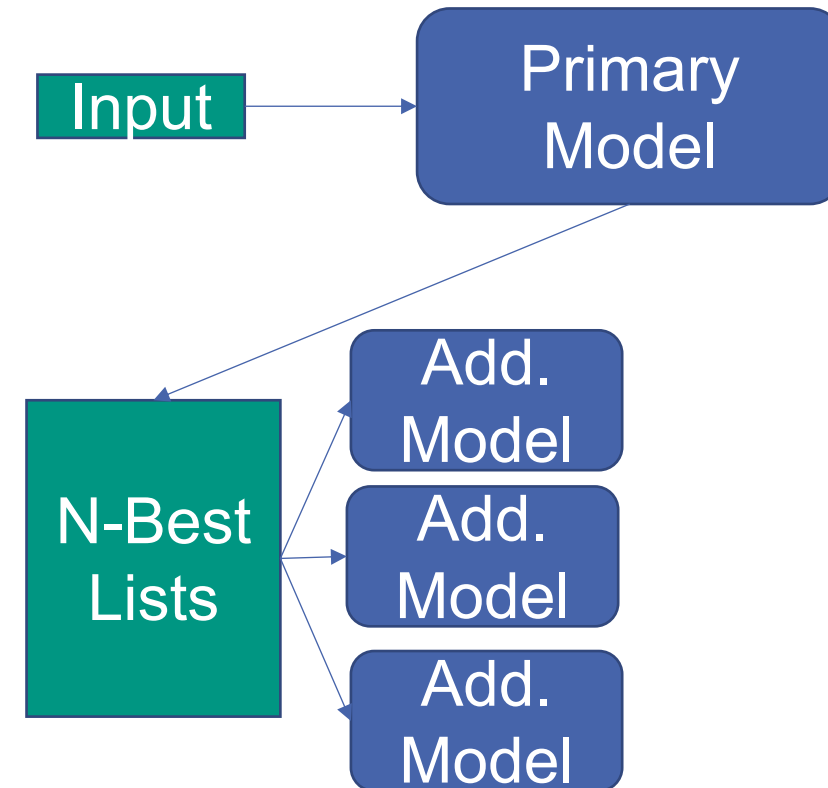
# Rescoring/Reranking

- Create N-Best List by primary model



# Rescoring/Reranking

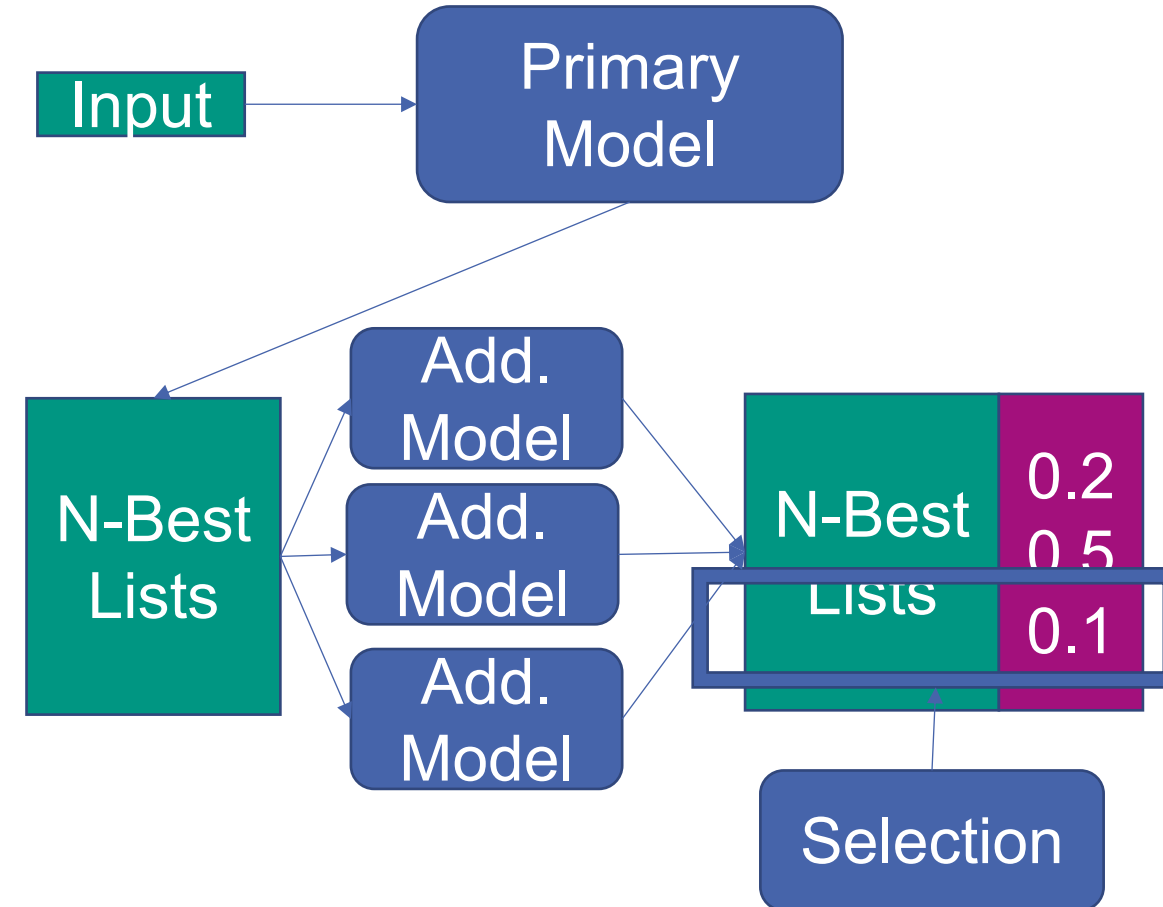
- Create N-Best List by primary model
- Rescore using additional models





# Rescoring/Reranking

- Create N-Best List by primary model
- Rescore using additional models
- Select best
  - Sum scores
  - Weights sum
    - Training using e.g. MERT



# Deversity Bias term

- N-Best List looks very similar
  - He never wanted to participate in any kind of confrontation.
  - He never wanted to take part in any kind of confrontation.
  - He never wanted to participate in any kind of argument.
  - He never wanted to take part in any kind of argument.
  - He never wanted to participate in any sort of confrontation.
  - He never wanted to take part in any sort of confrontation.
  - He never wanted to participate in any sort of argument.
  - He never wanted to take part in any sort of argument.
  - He never wanted to participate in any kind of controversy.
  - He never wanted to take part in any kind of controversy.
  - He never intended to participate in any kind of confrontation.
  - He never intended to take part in any kind of confrontation.
  - He never wanted to take part in some sort of confrontation.
  - He never wanted to take part in any sort of controversy.

# Deversity Bias term

- N-Best List looks very similar
- Single hypothesis generates too many of the surviving next hypothesis
- Add a cost based on rank
  - Most probable: no cost
  - Second most probable: cost  $c$
  - Third most probable: cost  $2c$

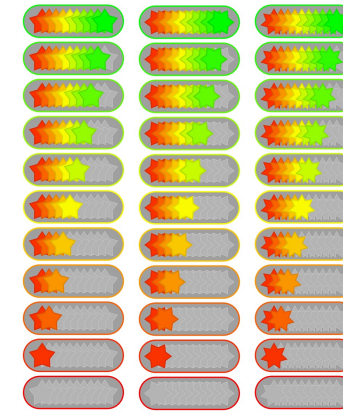
# Constrained Decoding

- The translation needs to fulfill additional constraints
- Example:
  - KIT → KIT (not Bausatz)
- Search only for hypothesis where the word KIT occurs
  - Alignment difficult

# Overview



Search



Ranking