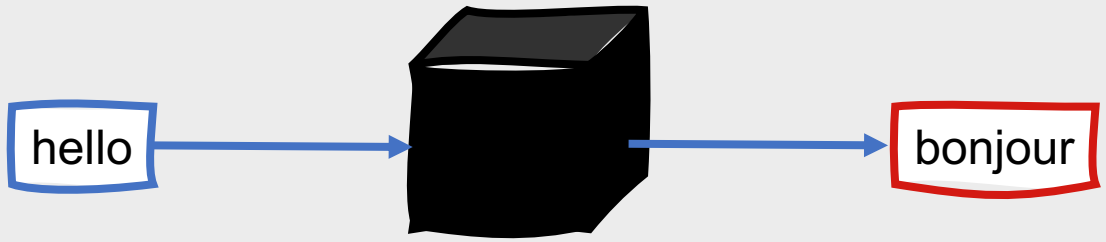
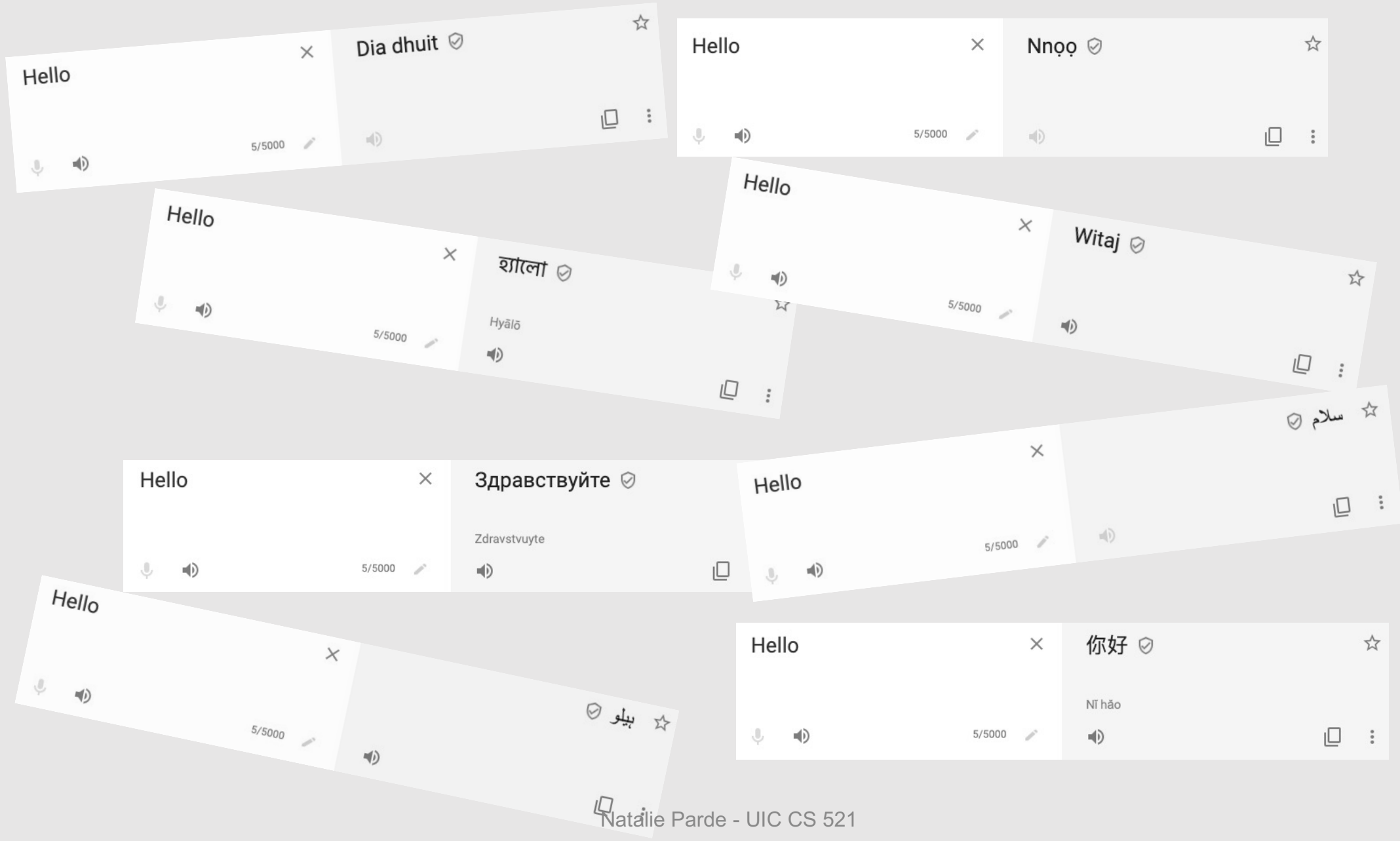
# Machine Translation and Encoder-Decoder Models

Natalie Parde
UIC CS 521

# What is machine translation?

- The process of automatically converting a text from one language to another

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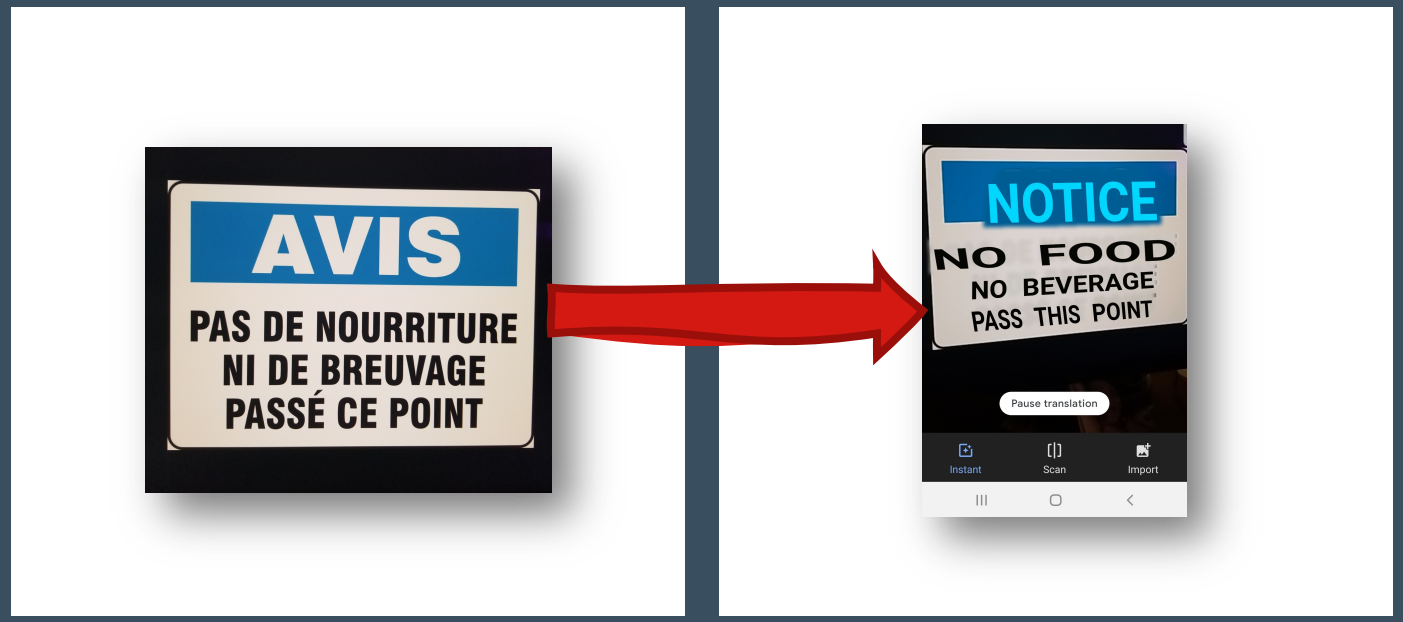
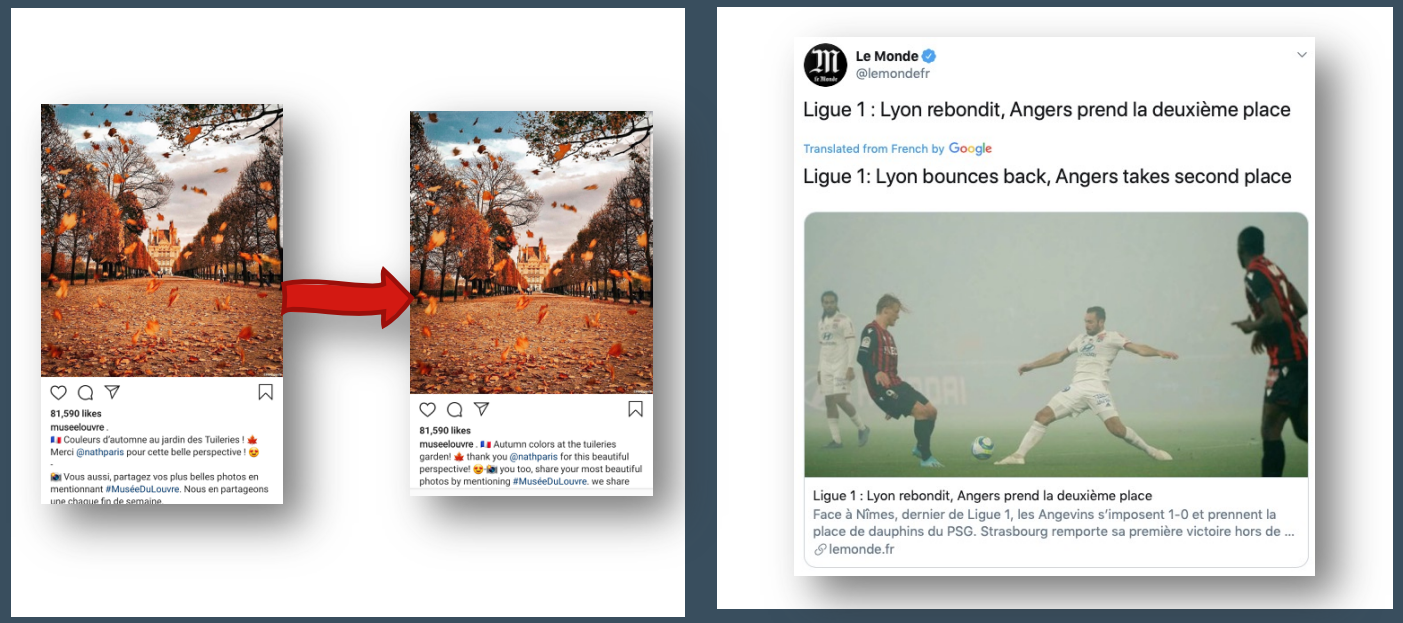






# Machine translation is increasingly ubiquitous, and useful in a wide variety of contexts!

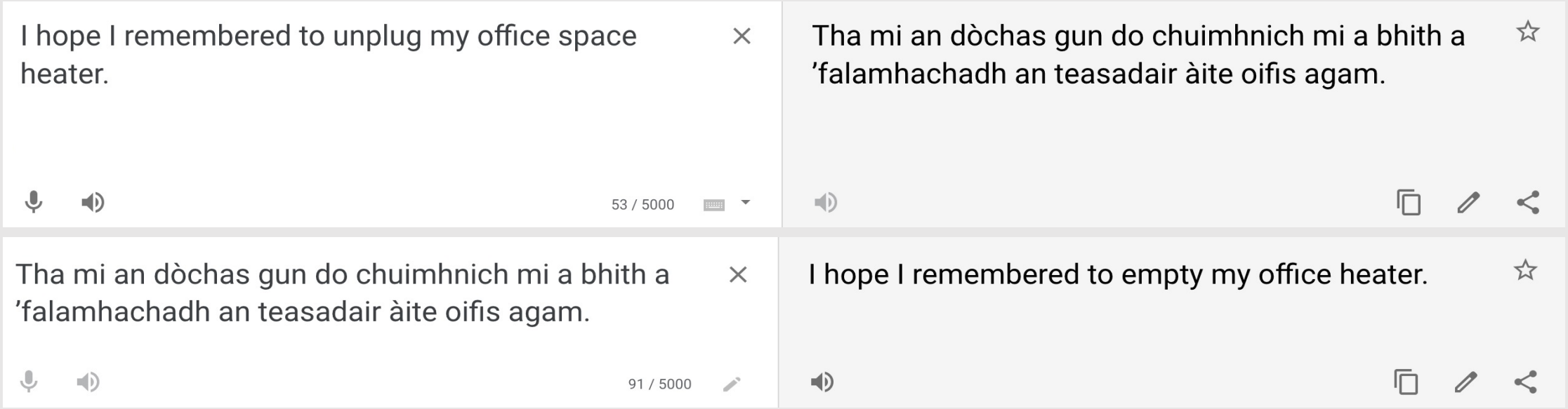
# Machine translation is also difficult, for a variety of reasons.

Structural and lexical differences between languages

Differences in word order

Morphological differences

Stylistic and cultural differences




**Creating high-quality translations requires a deep understanding of both the source and target language.**

# Computer-Aided Translation

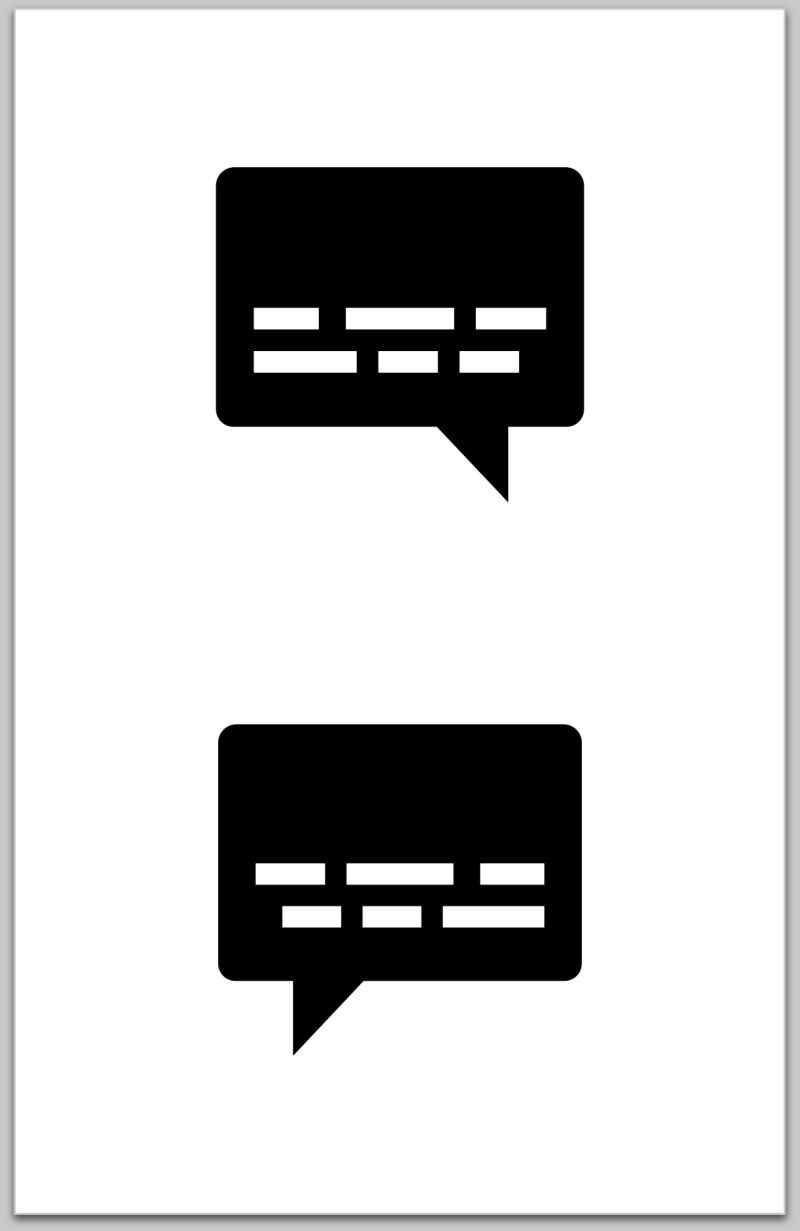
- Even poor translations are useful for some purposes!
- **Computer-Aided Translation:** Computers provide draft translations, which are then fixed in a post-editing phase by a human translator
- Effective for:
  - High volume jobs
  - Jobs requiring quick turnaround


Blender Manual: English


Blender Manual: French


Blender Manual: Spanish


Blender Manual: Arabic



# Cross-Linguistic Similarities and Differences

- **Typology:** The study of systematic cross-linguistic similarities and differences
  - Although some aspects of language are universal, others tend to differ
  - Differences between languages often have systematic structure

# Morphological Differences

## Number of morphemes per word

- **Isolating languages:** Each word generally has one morpheme
- **Polysynthetic languages:** Each word may have many morphemes

## Degree to which morphemes can be segmented

- **Agglutinative languages:** Morphemes have well-defined boundaries
- **Fusion languages:** Morphemes may be conflated with one another

# Syntactic Differences

- Primary difference between languages: Word order
  - **SVO languages:** Verb tends to come between the subject and object
  - **SOV languages:** Verb tends to come at the end of basic clauses
  - **VSO languages:** Verb tends to come at the beginning of basic clauses
- Languages with similar basic word order also tend to share other similarities
  - SVO languages generally have prepositions
  - SOV languages generally have postpositions

# Differences in Argument Structure and Linking

**Verb-framed languages:** Generally mark the direction of motion on the verb, leaving its satellites (particles, prepositional phrases, and adverbial phrases) to mark the manner of motion

**Satellite-framed languages:** Generally mark the direction of motion on the satellite, leaving the verb to mark the manner of motion

# Differences in Permissible Omissions

- Languages differ in terms of what components can be omitted from a sentence
- **Pro-Drop languages:** Can omit pronouns when talking about certain referents
- Some pro-drop languages permit more pronoun omission than others
  - **Referentially dense** and **sparse** languages
- Converting text from pro-drop languages (e.g., Japanese) to non-pro-drop languages (e.g., English) requires that all missing pronoun locations are identified and their appropriate **anaphors** recovered

# Other Differences

## Differences in noun-adjective order

- Blue house → Maison bleue

## Differences in homonymy and polysemy

## Differences in grammatical constraints

- Some languages require gender for nouns
- Some languages require gender for pronouns

## Lexical gaps

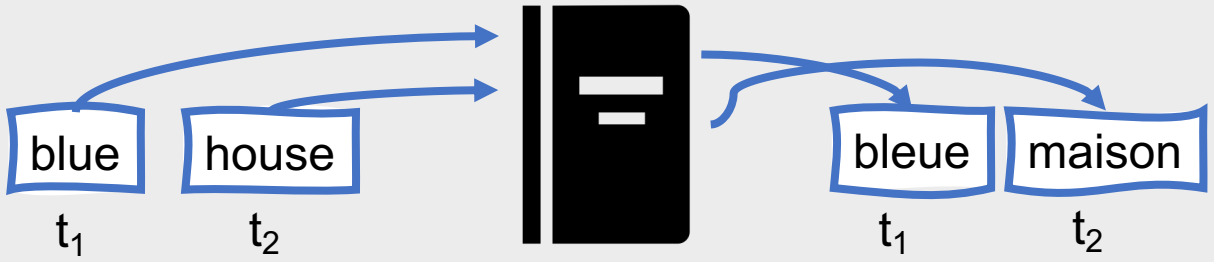
- No word or phrase in the target language can express the meaning of a word in the source language

# Machine Translation

- Classical Machine Translation
  - Direct translation
  - Transfer approaches
  - Interlingua approaches
  - Statistical methods
- Modern Machine Translation
  - Encoder-decoder models

# Classical Machine Translation

- **Direct translation**
  - Take a large bilingual dictionary
  - Proceed through the source text word by word
  - Translate each word according to the dictionary



# Direct Translation

No intermediate structures

Simple reordering rules may be applied

- Moving adjectives so that they are after nouns when translating from English to French

Dictionary entries may be relatively complex

- Tiny, rule-based programs for translating a word to the target language

# Direct Translation

**Pros:**

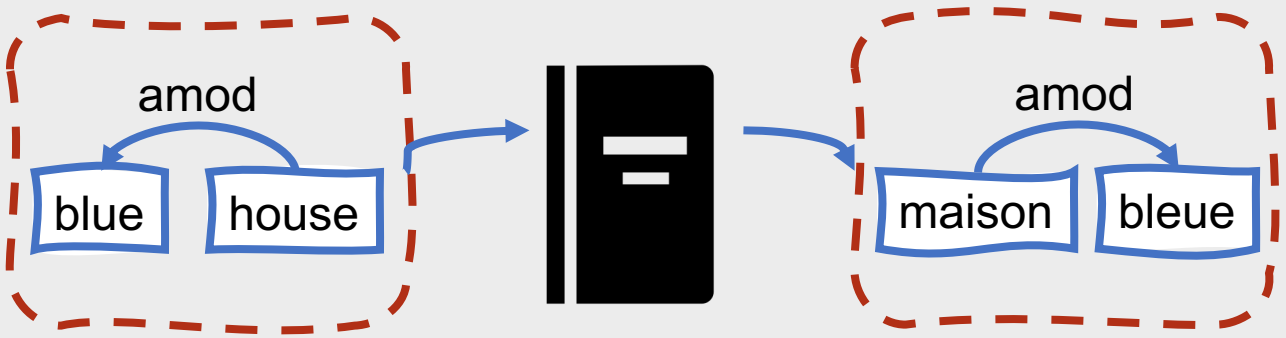
- Simple
- Easy to implement

**Cons:**

- Cannot reliably handle long-distance reorderings
- Cannot handle reorderings involving phrases or larger structures
- Too focused on individual words

# Classical Machine Translation

- **Transfer approaches**
  - Parse the input text
  - Apply rules to transform the source language parse structure into a target language parse structure

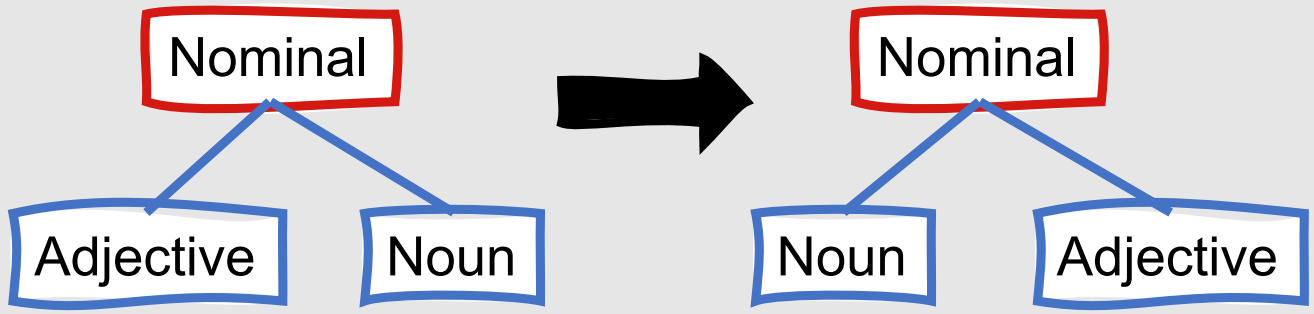


# Transfer Approaches

- Two subcategories of transformations:
  - Syntactic transfer
  - Lexical transfer

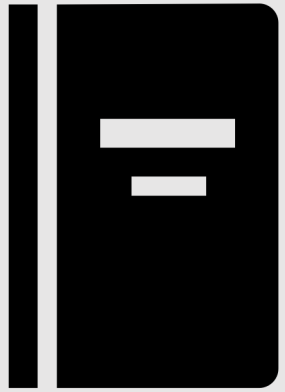
# Syntactic Transfer

- Modifies the source parse tree to resemble the target parse tree
- For some languages, may also include **thematic structures**
  - Directional or locative prepositional phrases vs. recipient prepositional phrases



# Lexical Transfer

- Generally based on a bilingual dictionary
  - As with direct translation, dictionary entries can be complex to accommodate many possible translations



# Transfer Approaches

## Pros:

- Can handle more complex language phenomena than direct translation

## Cons:

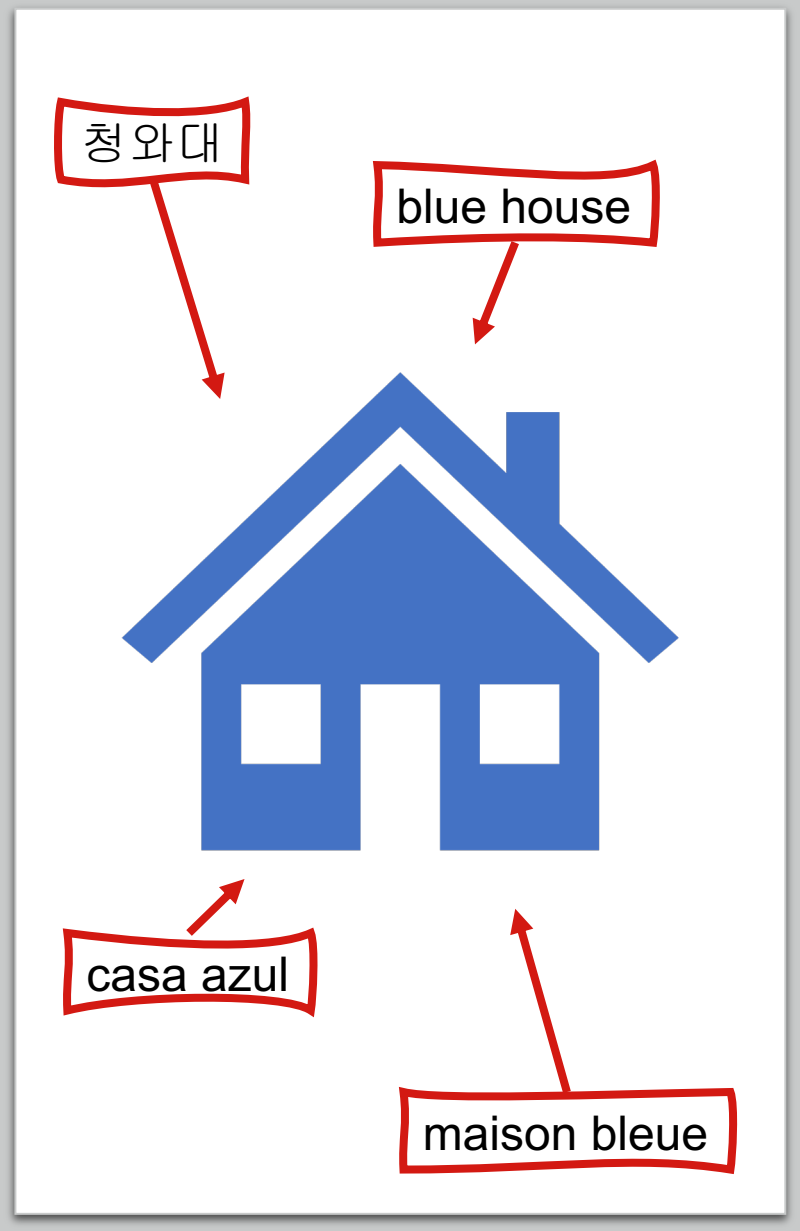
- Still not sufficient for many cases!

# Classical Machine Translation

- **Interlingua approaches**
  - Convert the source language text into an abstract meaning representation
  - Generate the target language text based on the abstract meaning representation

# Interlingua Approaches

- Goal: Represent all sentences that mean the same thing in the same way, regardless of language
- What kind of representation scheme should be used?
  - Classical approaches:
    - First-order logic
    - Semantic primitives
    - Event-based representation
  - More recently, neural models learn vector representations for this purpose



# Interlingua Approaches

- Require more analysis work than transfer approaches
  - Semantic analysis
  - Sentiment analysis
- No need for syntactic or lexical transformations

# Interlingua Approaches

**Pros:**

- Direct mapping between meaning representation and lexical realization
- No need for transformation rules

**Cons:**

- Extra (often unnecessary) work
  - Classical approaches require an exhaustive analysis and formalization of the semantics of the domain

# Statistical Machine Translation

- Models automatically learn to map from the source language to the target language
  - Doesn’t require intermediate transformation rules
  - Doesn’t require an explicitly defined internal meaning representation

# Statistical Machine Translation

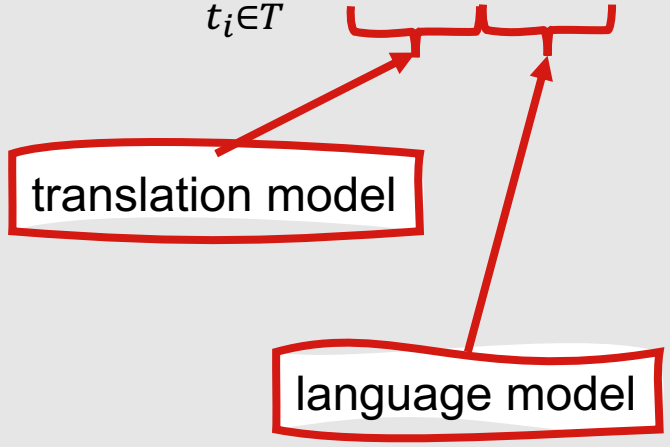
- Goal: Produce an output that maximizes some function representing translation **faithfulness** and **fluency**
- One possible approach: **Bayesian noisy channel model**
  - Assume a possible target language translation $t_i$ and a source language sentence $s$
  - Select the translation $t'$ from the set of all possible translations $t_i \in T$ that maximizes the probability $P(t_i|s)$

# Bayesian Noisy Channel Model

- To find P($t_i$|$s$), we can use Bayes rule:
  - $t' = \underset{t_i \in T}{\operatorname{argmax}} P(t_i \,|s)$
  - $t' = \underset{t_i \in T}{\operatorname{argmax}} \frac{P(s|t_i)P(t_i)}{P(s)}$
- We can ignore the denominator ($P(s)$) since it will remain the same for all possible translations
- Thus:
  - $t' = \underset{t_i \in T}{\operatorname{argmax}} P(s|t_i)P(t_i)$

# This means that we need to consider two separate components.

$$t' = \underset{t_i \in T}{\operatorname{argmax}} P(s|t_i)P(t_i)$$




- The language model is just like the language models used for other NLP tasks
- One common type of translation model is the **phrase-based translation model**

# The Phrase-Based Translation Model

- Computes the probability that a given translation $t_i$ generates the original sentence $s$ based on its **constituent phrases**
- Intuition: Phrases, as well as single words, are fundamental units of translation
  - Often entire phrases need to be translated and moved as a unit

# Stages of Phrase-Based Translation

01

Group the words from the source sentence into phrases

02

Translate each source phrase into a target language phrase

03

(Optionally) reorder the target language phrases

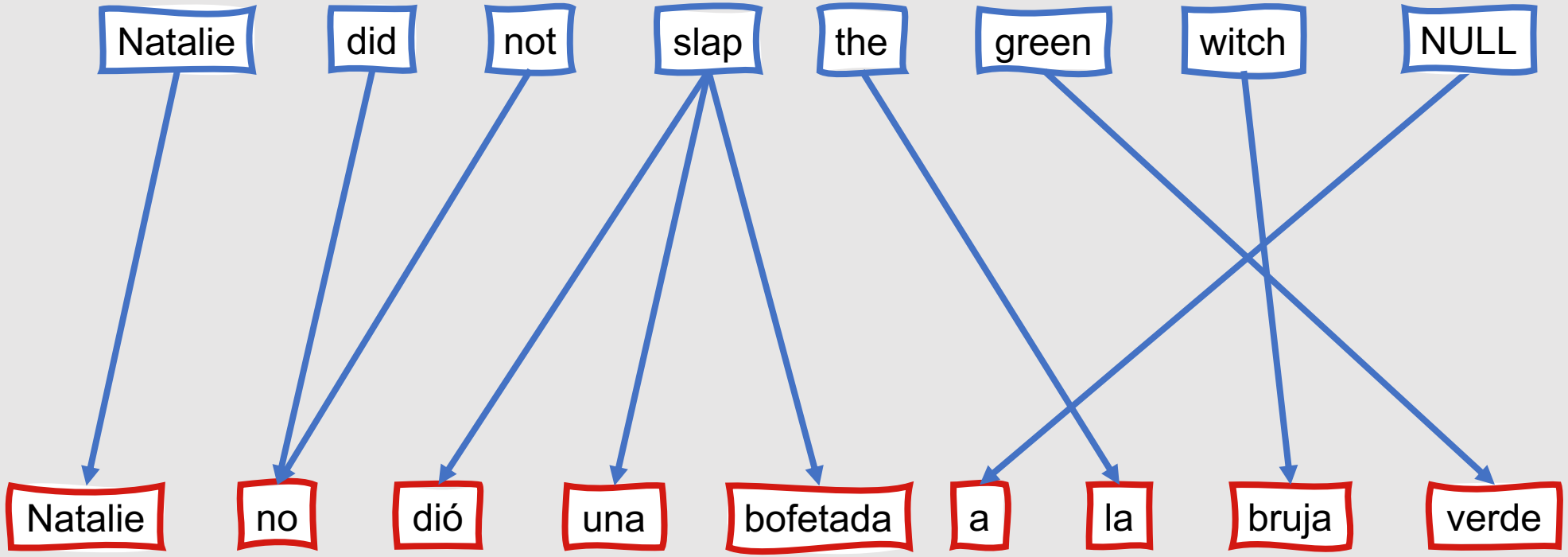
# Probability in Phrase-Based Translation Models

- Relies on two probabilities:
  - **Translation probability**
    - Probability of generating a source language phrase from a target language phrase, $\phi(\overline{t_i}, \overline{s_i})$
  - **Distortion probability**
    - Probability of two consecutive target language phrases being separated in the source language by a word span of a particular length, $d(a_i - b_{i-1})$

# How do we learn the probabilities for this model?

- We need to train two sets of parameters:
  - $\phi(\dot{t}_i, \dot{s}_i)$
  - $d(a_i - b_{i-1})$
- We learn these based on large bilingual training sets in which we know which phrase in a source sentence is translated to which phrase in a target sentence
- These mappings are called **phrase alignments**

# Alignment in Machine Translation



# Decoding for Phrase-Based Machine Translation

- Aligned phrases can be stored in a **phrase-translation** table
- **Decoding algorithms** can then search through this table to find the overall translation that maximizes the phrase translation probabilities

# Machine Translation

- Classical Machine Translation
  - Direct translation
  - Transfer approaches
  - Interlingua approaches
  - Statistical methods
- Modern Machine Translation
  - Encoder-decoder models

- Generate **contextually-appropriate**, **arbitrary-length** output sequences
- Particularly useful for:
  - Machine translation
  - Summarization
  - Question answering
  - Dialogue modeling

# Encoder-Decoder Models

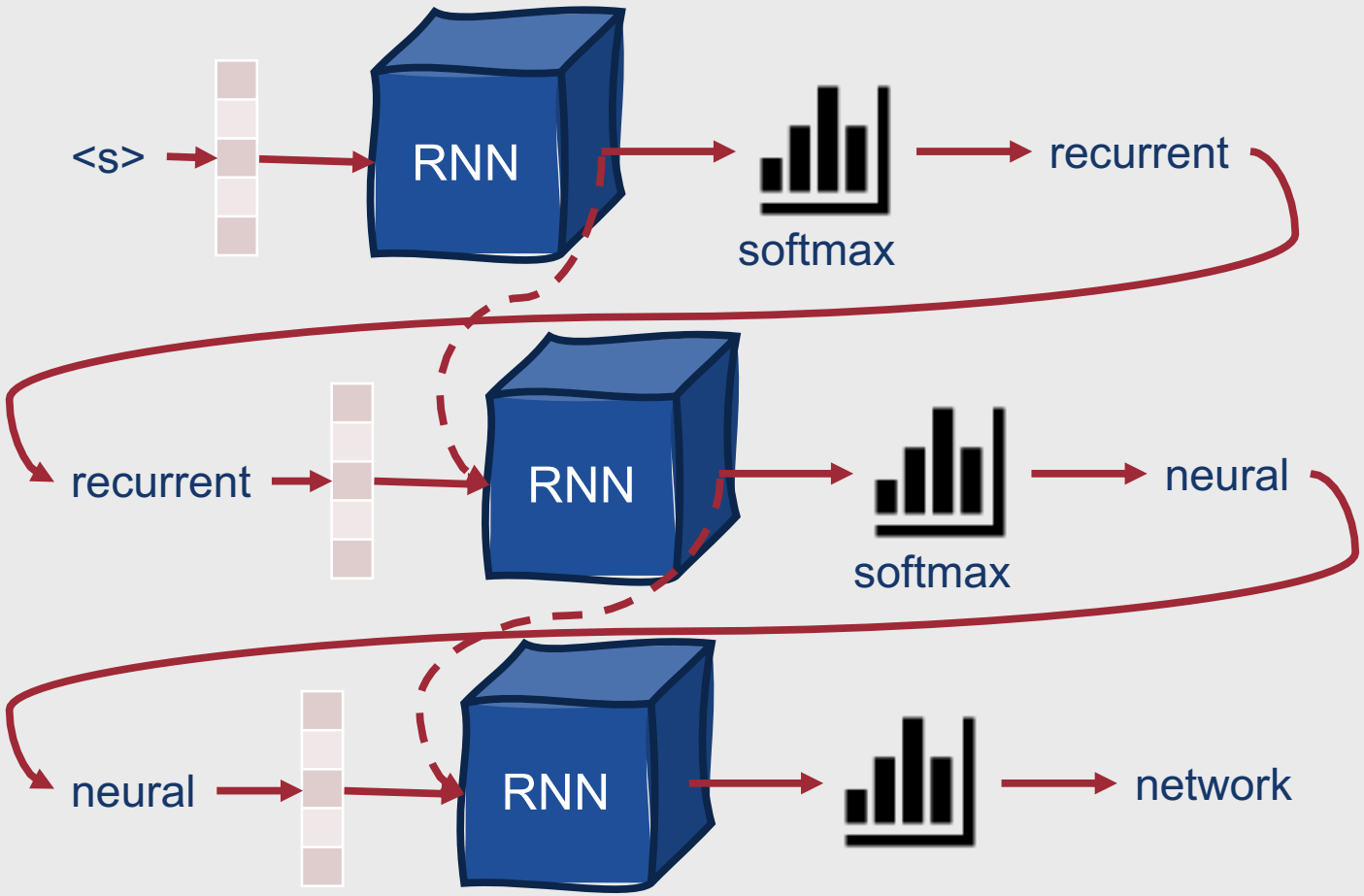
# Encoder-Decoder Models

- Basic premise:
  - Use a neural network to **encode an input to an internal representation**
  - Pass that internal representation as input to a second neural network
  - Use that neural network to **decode the internal representation to a task-specific output sequence**
- Usually, the encoder and decoder are both some type of **RNN**
- This method allows networks to be trained in an **end-to-end** fashion

# Where did this idea come from?

Recall our discussion of autoregressive generation:

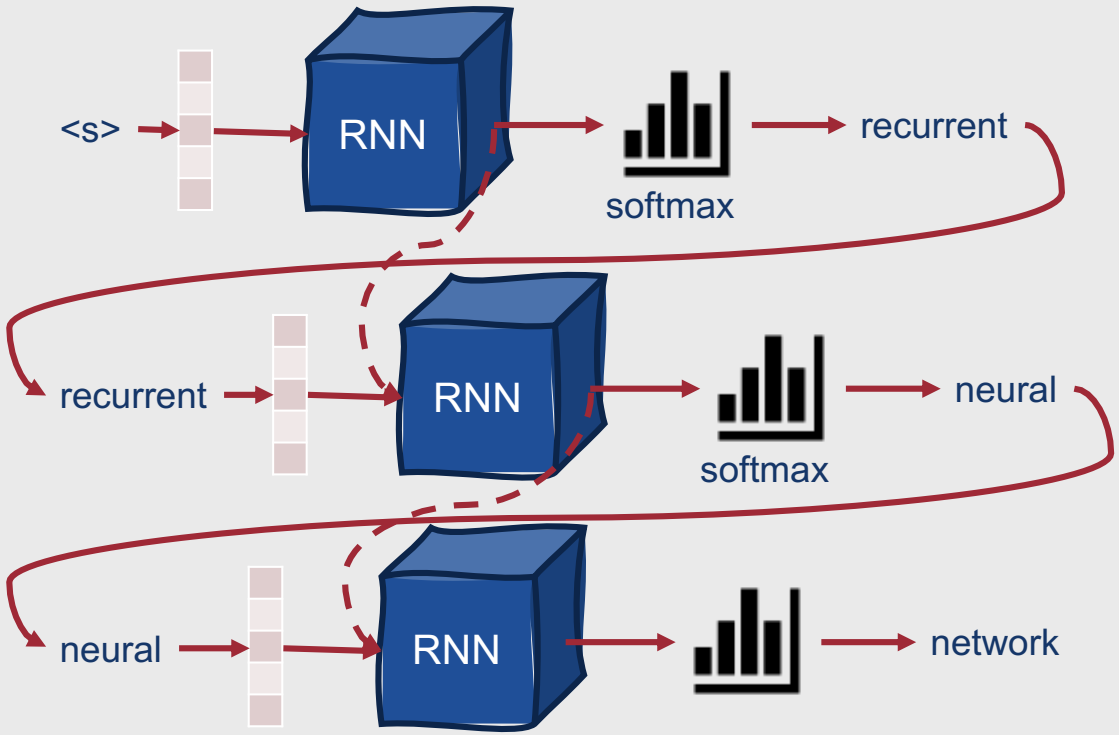
- Start with a seed token (e.g., <s>)
- Predict the most likely next word in the sequence
- Use that word as input at the next timestep
- Repeat until an end token (or max length) is reached

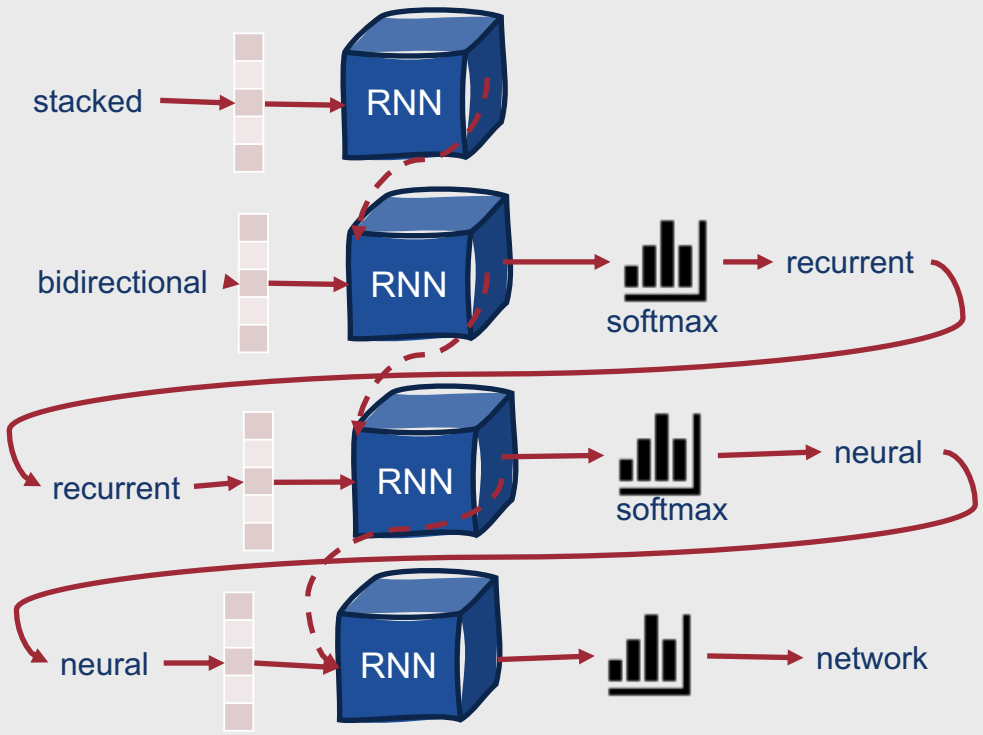


# Slight variation to this idea….

- Rather than generating a sentence from scratch, the model can generate a sentence given a prefix
  - Pass the specified prefix through the language model, in sequence
  - End with the hidden state corresponding to the last word of the prefix
  - Start the autoregressive process at that point
- **Goal: Output sequence should be a reasonable completion of the prefix**

# Updated Autoregressive Generation



# We can build upon this idea to transform one type of sequence to another.

- Machine translation example:
  1. Take a **sequence of text from Language #1**
  2. Take the **translation of that text from Language #2**
  3. **Concatenate the two sequences**, separated by a marker
  4. Use these concatenated sequences to **train the autoregressive model**
  5. Test the model by **passing in only the first part of a concatenated sequence** (text from Language #1) and checking to see what the generated completion (text from Language #2) looks like

# Intuition: Machine Translation

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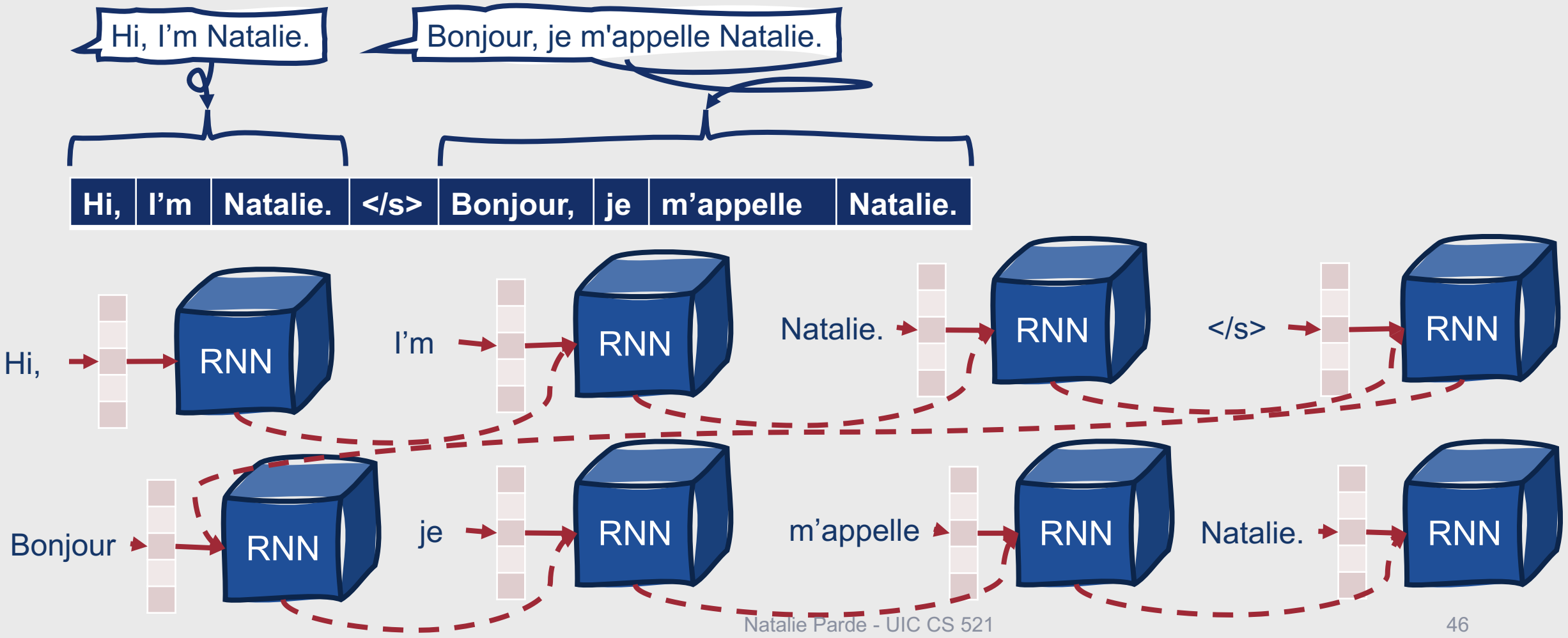
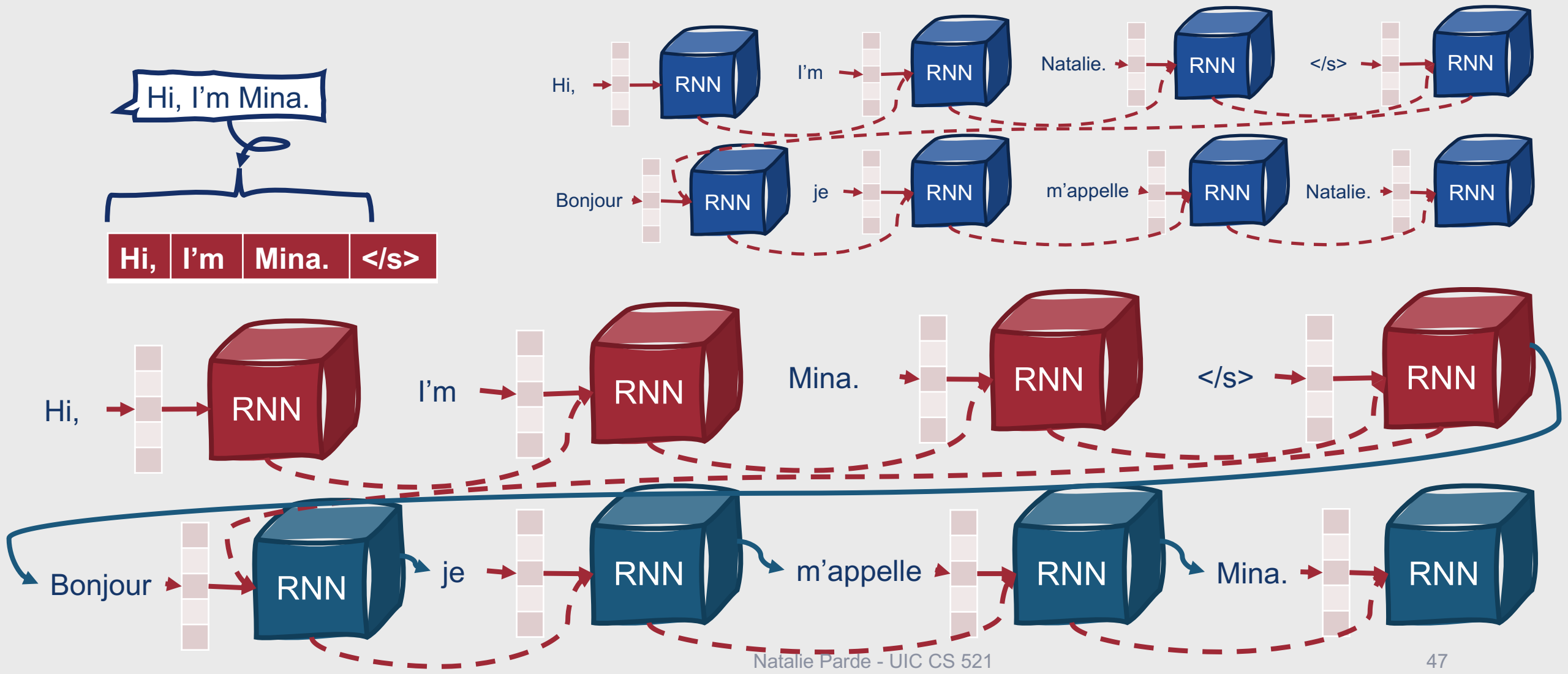


# Intuition: Machine Translation



# This intuition forms the basis of encoder-decoder networks.

- Key elements of an encoder-decoder network:
  - **Encoder:** Generates a contextualized representation of the input
  - **Decoder:** Takes the contextualized representation and autoregressively generates a sequence of outputs

# More formally….

- **Encoder**
  - Accepts an input sequence, $x_1^n$
  - Generates a sequence of contextualized representations, $h_1^n$
- **Context vector**
  - A function, $c$, of $h_1^n$ that conveys the basic meaning of $x_1^n$ to the decoder
  - (Might just be equivalent to $h_1^n$)
- **Decoder**
  - Accepts $c$ as input
  - Generates an arbitrary-length sequence of hidden states, $h_1^m$, from which a corresponding sequence of output states $y_1^m$ can be obtained

# Encoders

- Can be any type of neural network
  - Feedforward network
  - CNN
  - RNN
  - LSTM/BiLSTM
  - GRU/BiGRU
  - Transformer


- These networks can be stacked on top of one another

# Decoders

- Need to perform autoregressive generation to produce the output sequence
- Can be any type of sequential network
  - RNN
  - LSTM
  - GRU
  - Transformer

# Decoders

- Formally….
  - $c = h_n^e$
  - $h_0^d = c$

  - $h_t^d = g(\widehat{y_{t-1}}, h_{t-1}^d)$
  - $z_t = f(h_t^d)$
  - $y_t = \text{softmax}(z_t)$

# Decoders

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Final hidden state of the encoder

# Decoders

- Formally….
  - $c = h_n^e$
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  - $h_t^d = g(\widehat{y_{t-1}}, h_{t-1}^d)$
  - $z_t = f(h_t^d)$
  - $y_t = \text{softmax}(z_t)$

First hidden state of the decoder

# Decoders

- Formally….
  - $c = h_n^e$
  - $h_0^d = c$
  - $h_t^d = g(\widehat{y_{t-1}}, h_{t-1}^d)$
  - $z_t = f(h_t^d)$
  - $y_t = \text{softmax}(z_t)$

Embedding for the output sampled from the previous step

Some type of RNN

# Decoders

- Formally….
  - $c = h_n^e$
  - $h_0^d = c$

  - $h_t^d = g(\widehat{y_{t-1}}, h_{t-1}^d)$
  - $z_t = f(h_t^d)$
  - $y_t = \text{softmax}(z_t)$

Regular ending steps (activation function applied to hidden state outputs, and softmax applied to activation outputs)

# A couple useful extensions….

- Formally….
  - $c = h_n^e$
  - $h_0^d = c$
  - $h_t^d = g(\widehat{y_{t-1}}, h_{t-1}^d) \rightarrow h_t^d = g(\widehat{y_{t-1}}, h_{t-1}^d, c)$
  - $z_t = f(h_t^d)$
  - $y_t = \text{softmax}(z_t)$

Make the context vector available at each timestep when decoding, so that its influence doesn't diminish over time

# A couple useful extensions….

- Formally….
  - $c = h_n^e$
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  - $h_t^d = g(\widehat{y_{t-1}}, h_{t-1}^d) \rightarrow h_t^d = g(\widehat{y_{t-1}}, h_{t-1}^d, c)$
  - $z_t = f(h_t^d)$
  - $y_t = \text{softmax}(z_t) \rightarrow y_t = \text{softmax}(\widehat{y_{t-1}}, z_t, c)$

Condition output on not only the hidden state, but the previous output and encoder context (easier to keep track of what's been generated already)

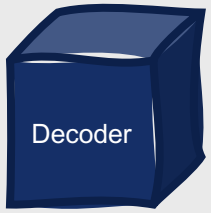
# What other ways can we improve the decoder's output quality?

- **Beam search**
- Improved **context vector**
  - Final hidden state tends to be more focused on the end of the input sequence
  - Can be addressed by using bidirectional RNNs, summing the encoder hidden states, or averaging the encoder hidden states

# Beam Search

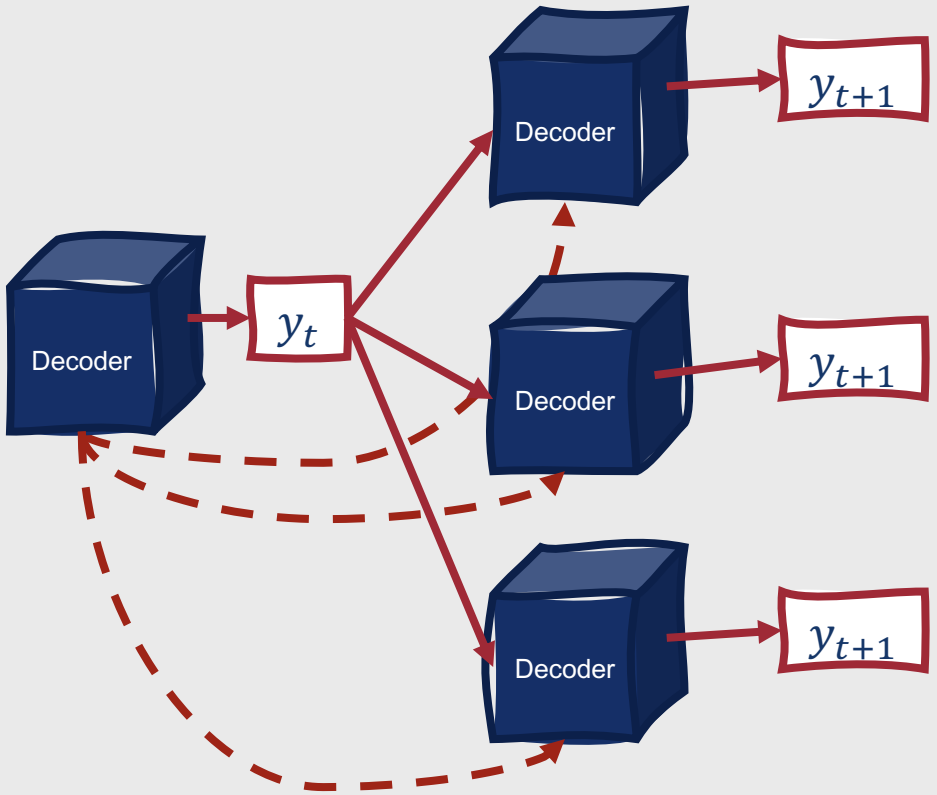
- Selects from multiple possible outputs by framing the task as a **state space search**
- Combines **breadth-first search** with a **heuristic filter**
  - Continually prunes search space to stay a fixed size (**beam width**)
- Results in a set of *b* **hypotheses**, where *b* is the beam width

# How does beam search work?




Beam Size = 3

# How does beam search work?

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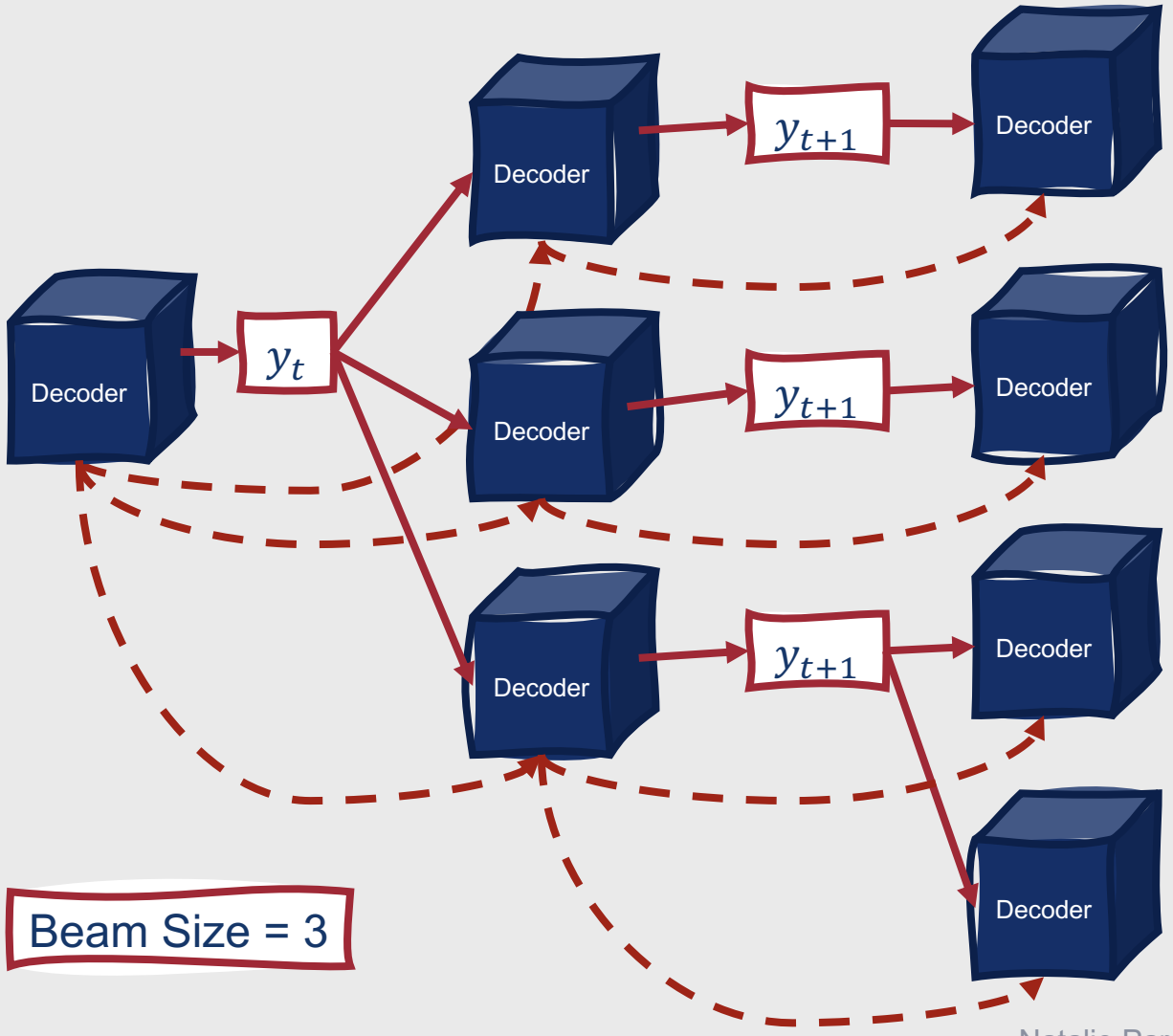

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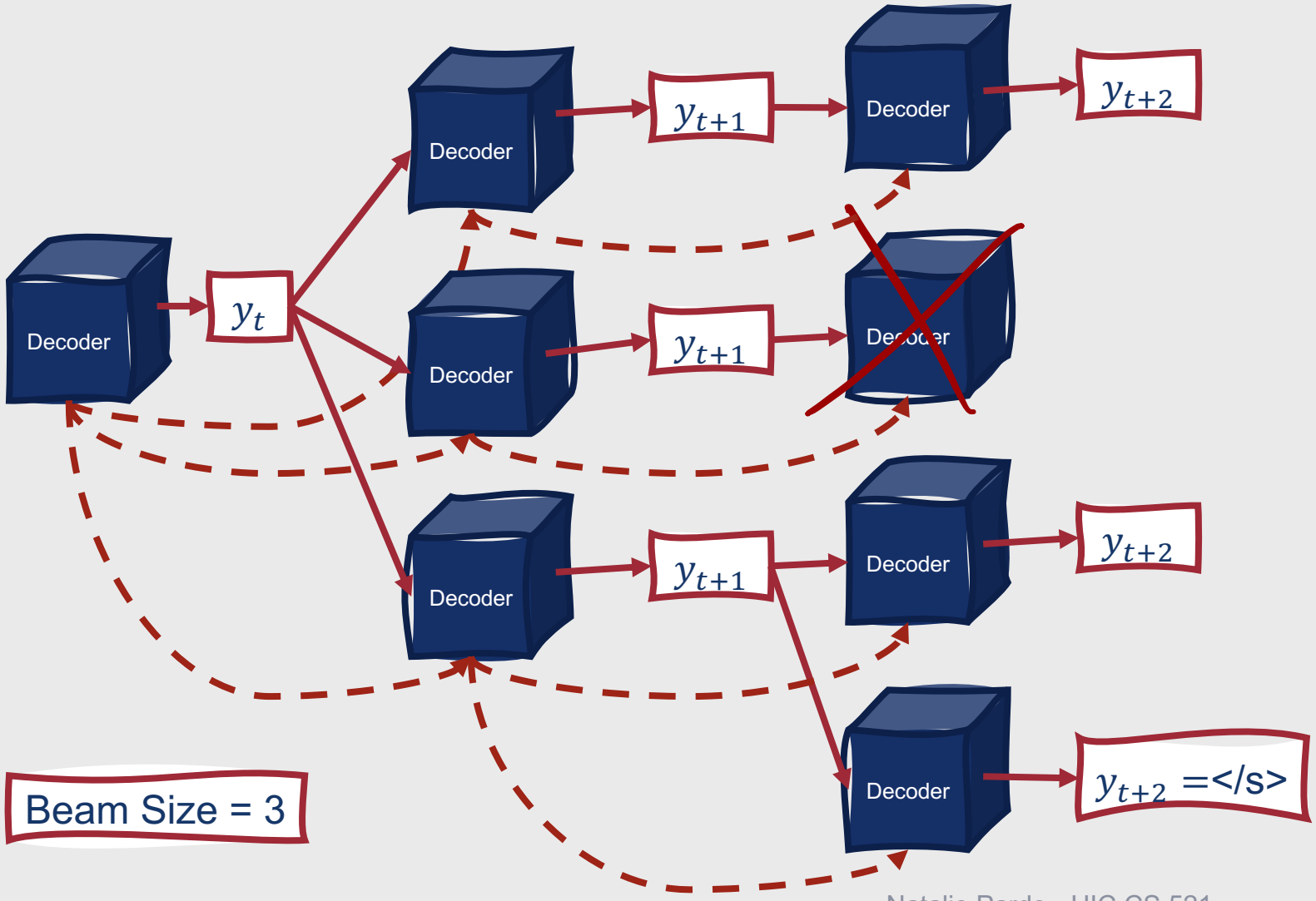

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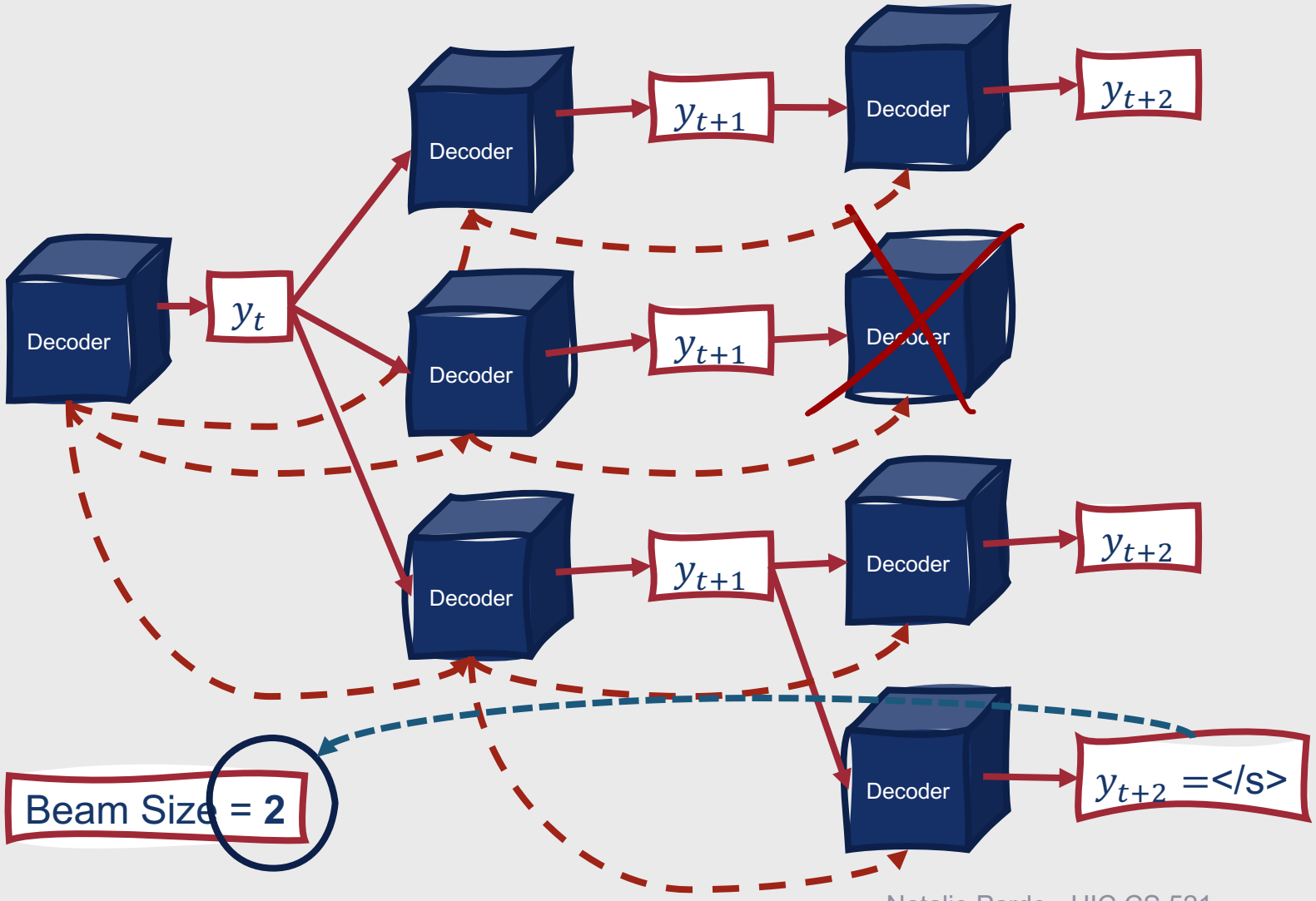

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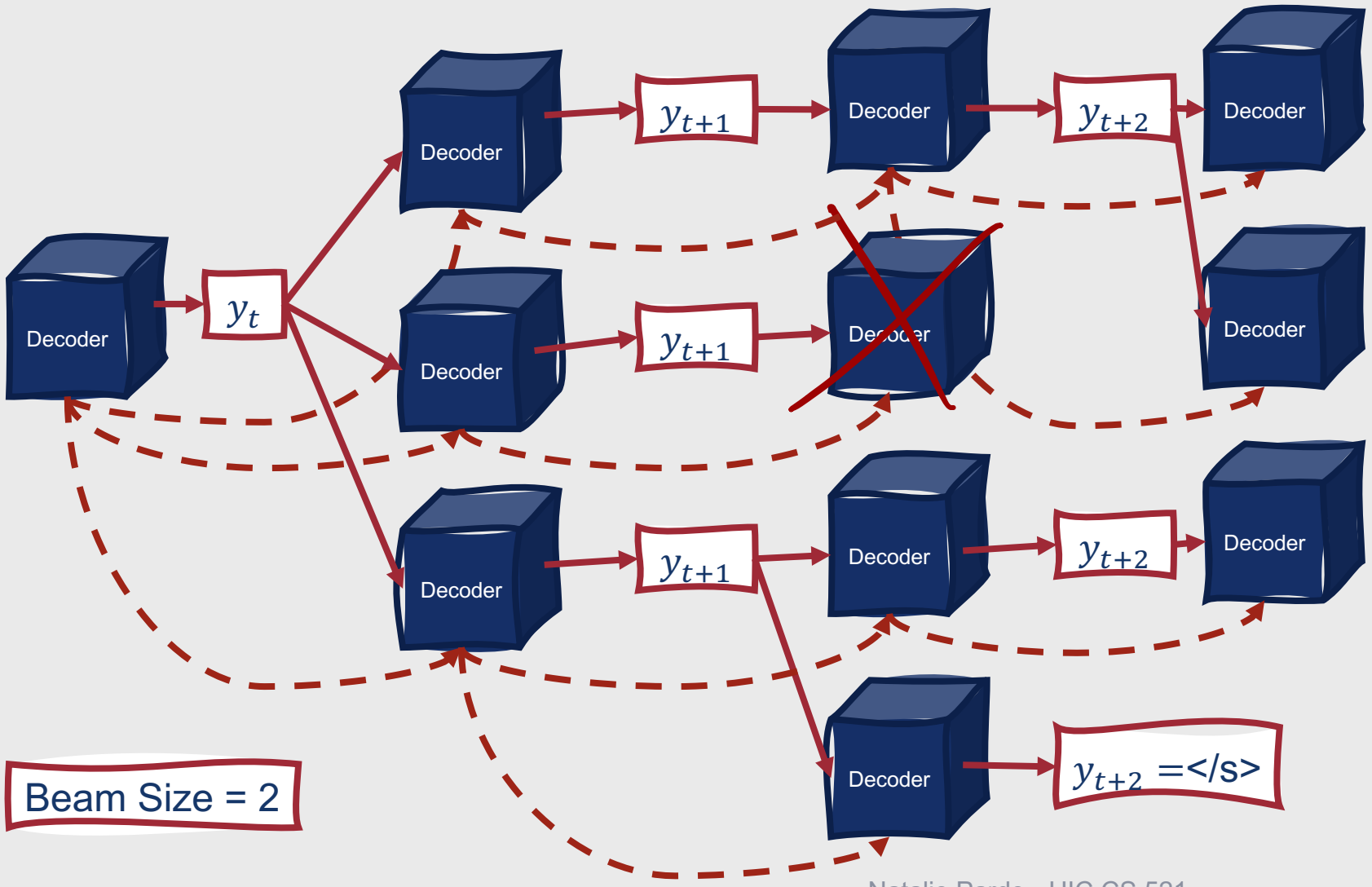

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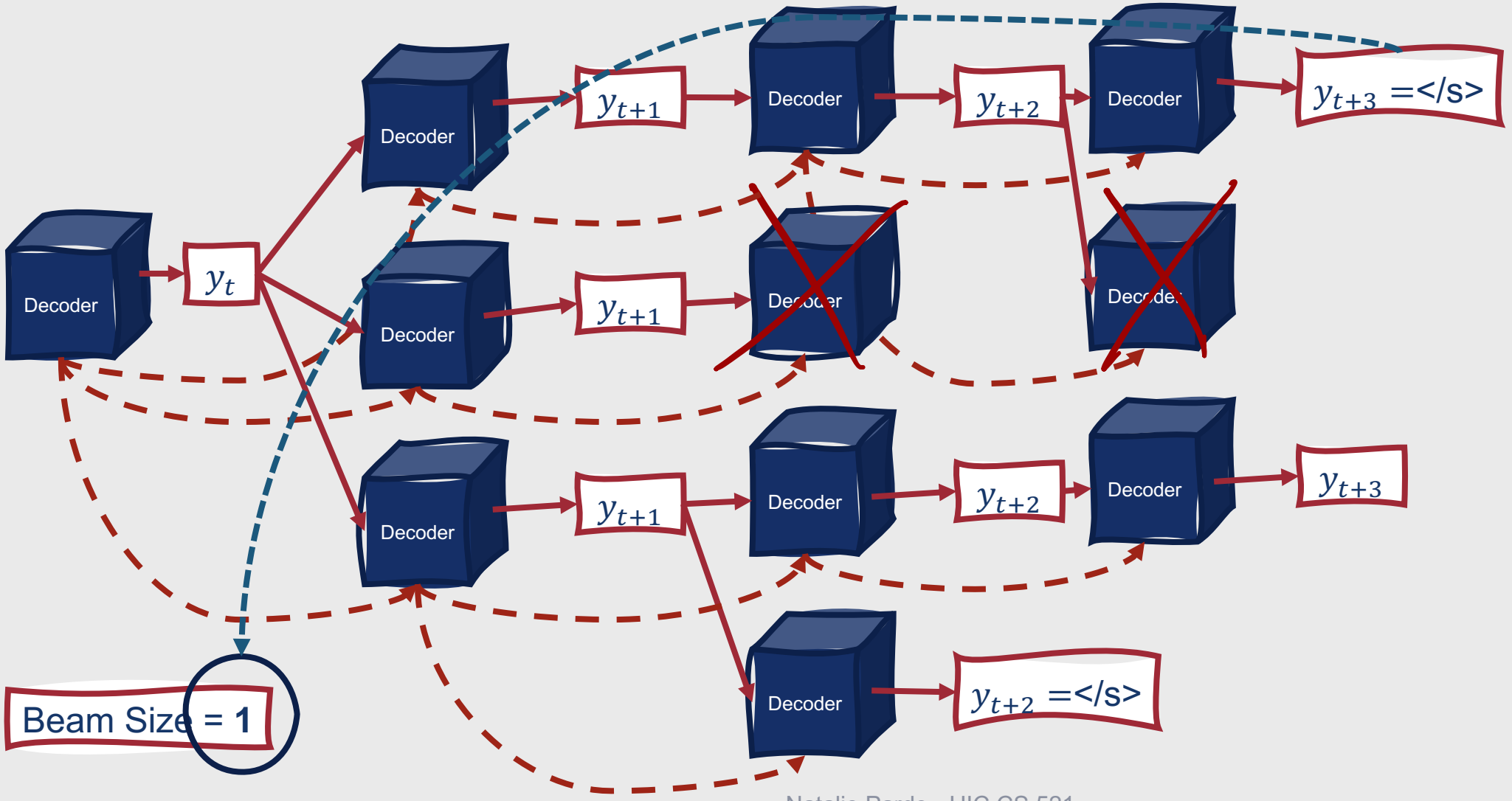

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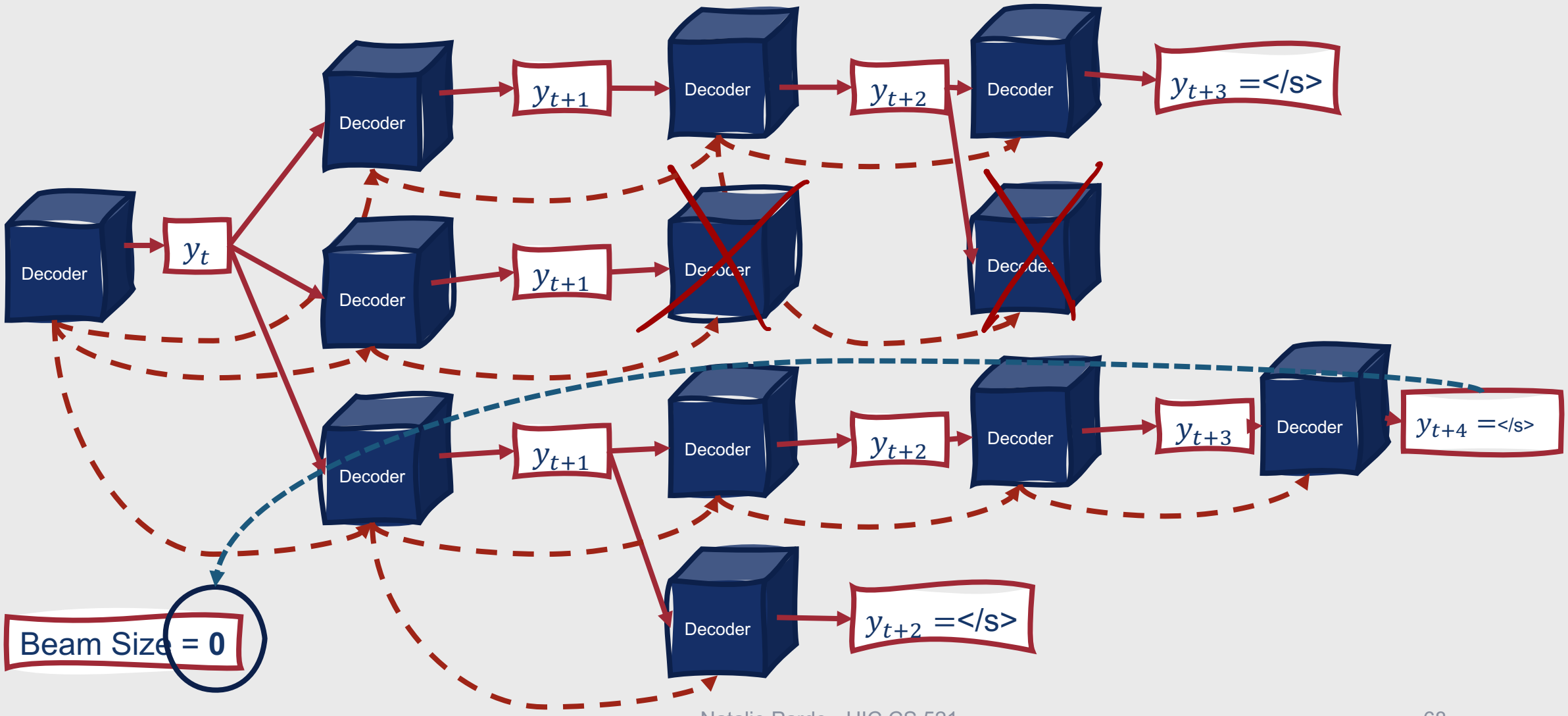

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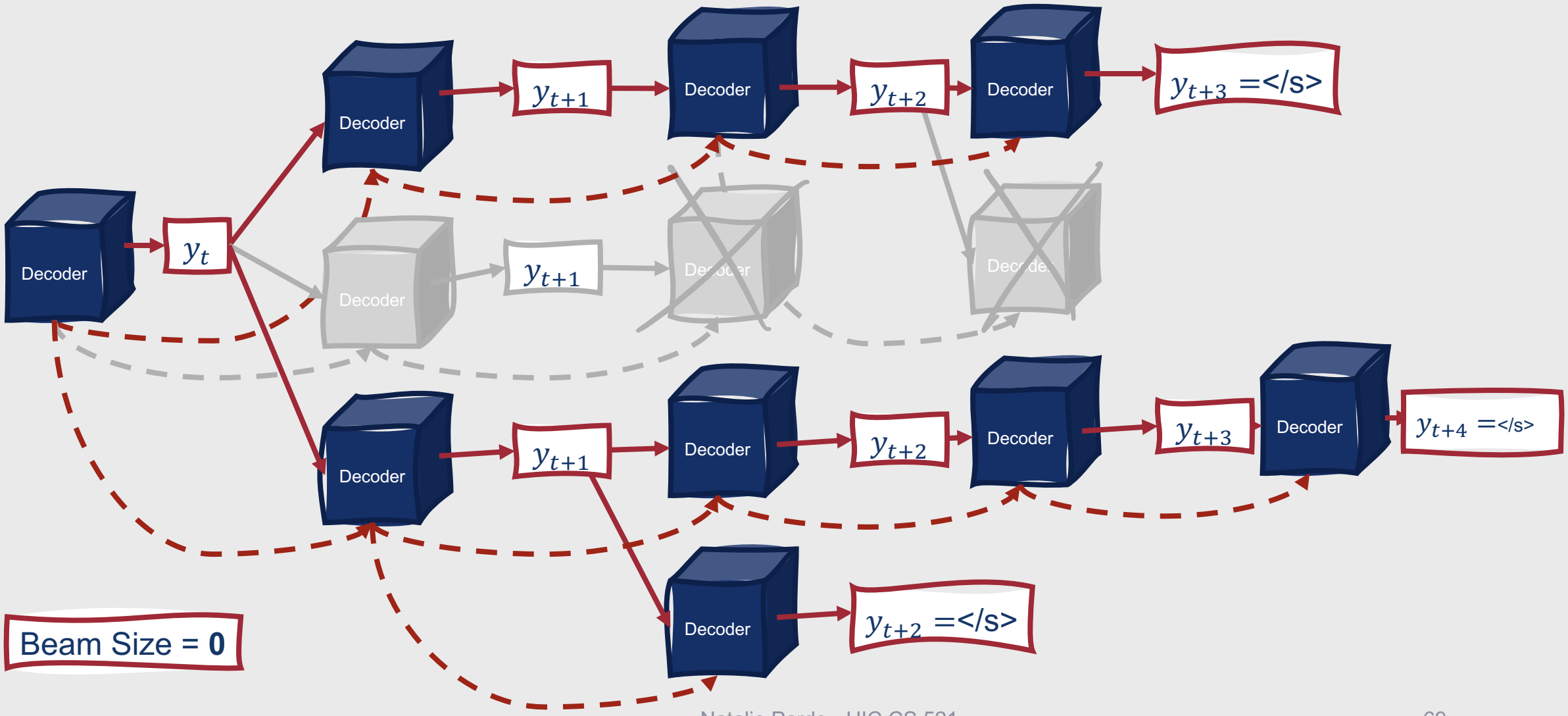


# How do we choose a best hypothesis?

- Probabilistic scoring scheme
- Pass all or a subset of hypotheses to a downstream application

# So far, the encoder context vectors we've seen have been simple and static.

- Can we do better?
  - Yes 🙂

# Attention Mechanism

- Takes entire encoder context into account
- Dynamically updates during the course of decoding
- Can be embodied in a fixed-size vector

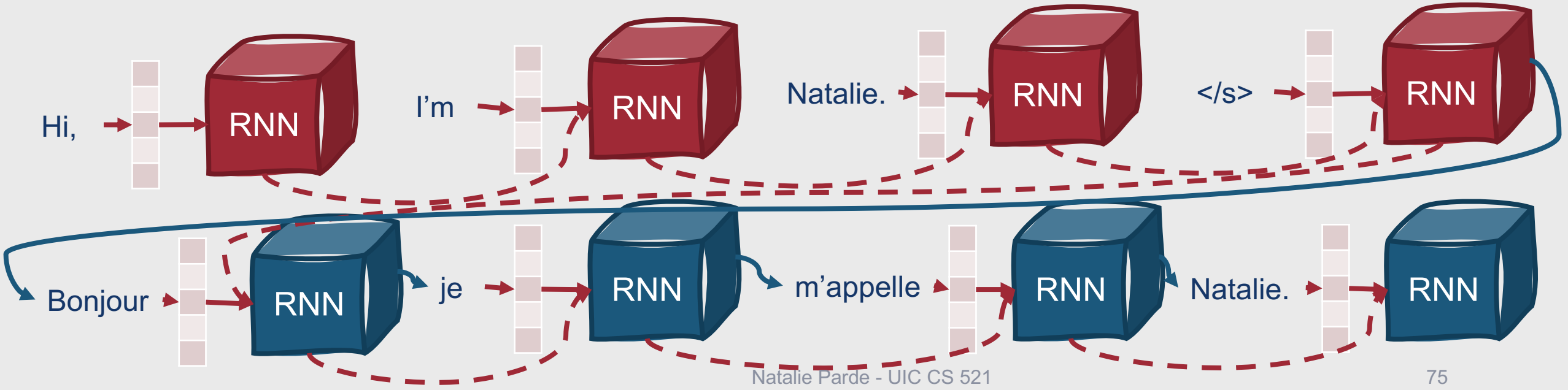
# Recall….

- We've already made our context vector available at each timestep when decoding
  - $h_t^d = g(\widehat{y_{t-1}}, h_{t-1}^d, c)$
- The first step in creating our attention mechanism is to update our hidden state such that it is conditioned on an updated context vector with each decoding step
  - $h_t^d = g(\widehat{y_{t-1}}, h_{t-1}^d, c_t)$

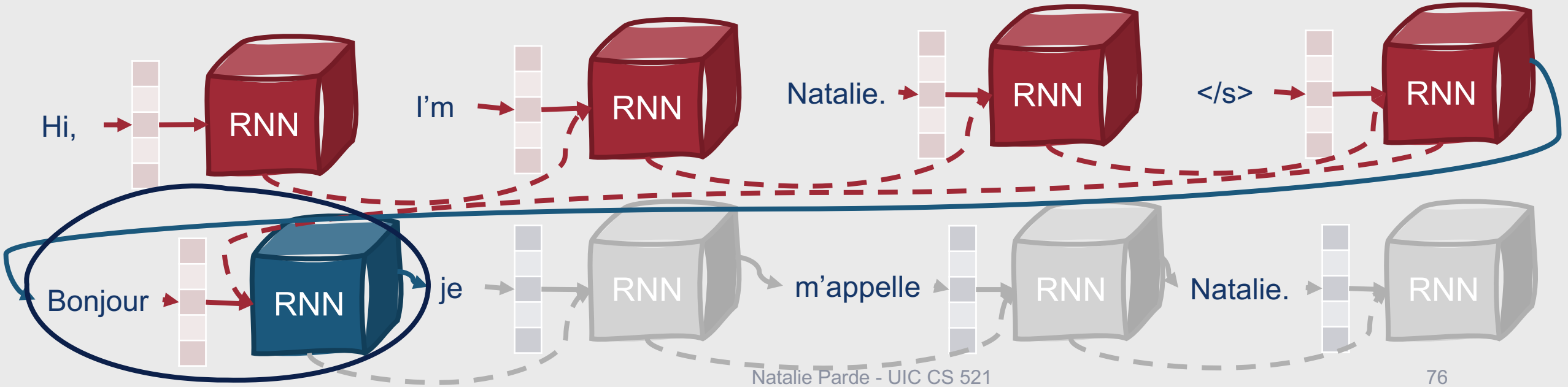
# How do we dynamically create a new context vector at each step?

- Compute a vector of scores that capture the relevance of each encoder hidden state to the decoder hidden state, $h_{i-1}^{d}$
  - $score\left(h_{i-1}^{d}, h_{j}^{e}\right) = h_{i-1}^{d} \cdot h_{j}^{e}$

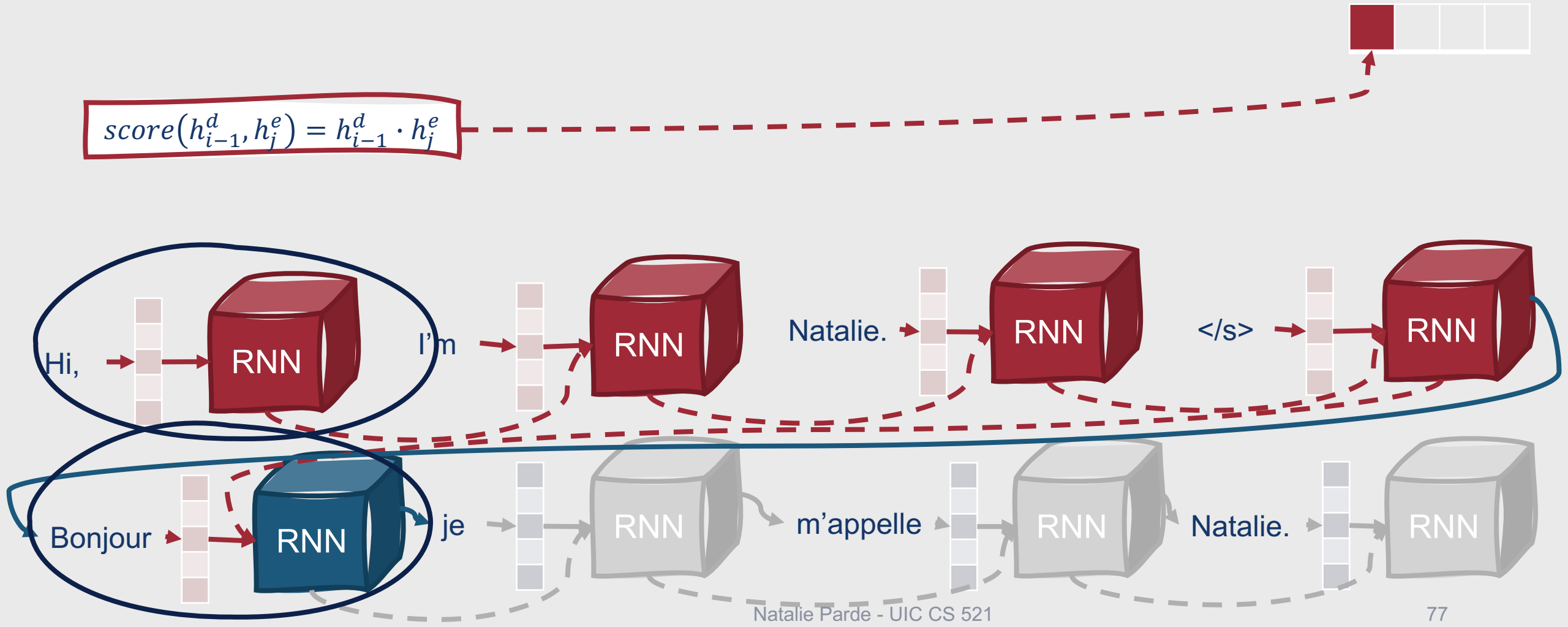
# Vector of Context Scores



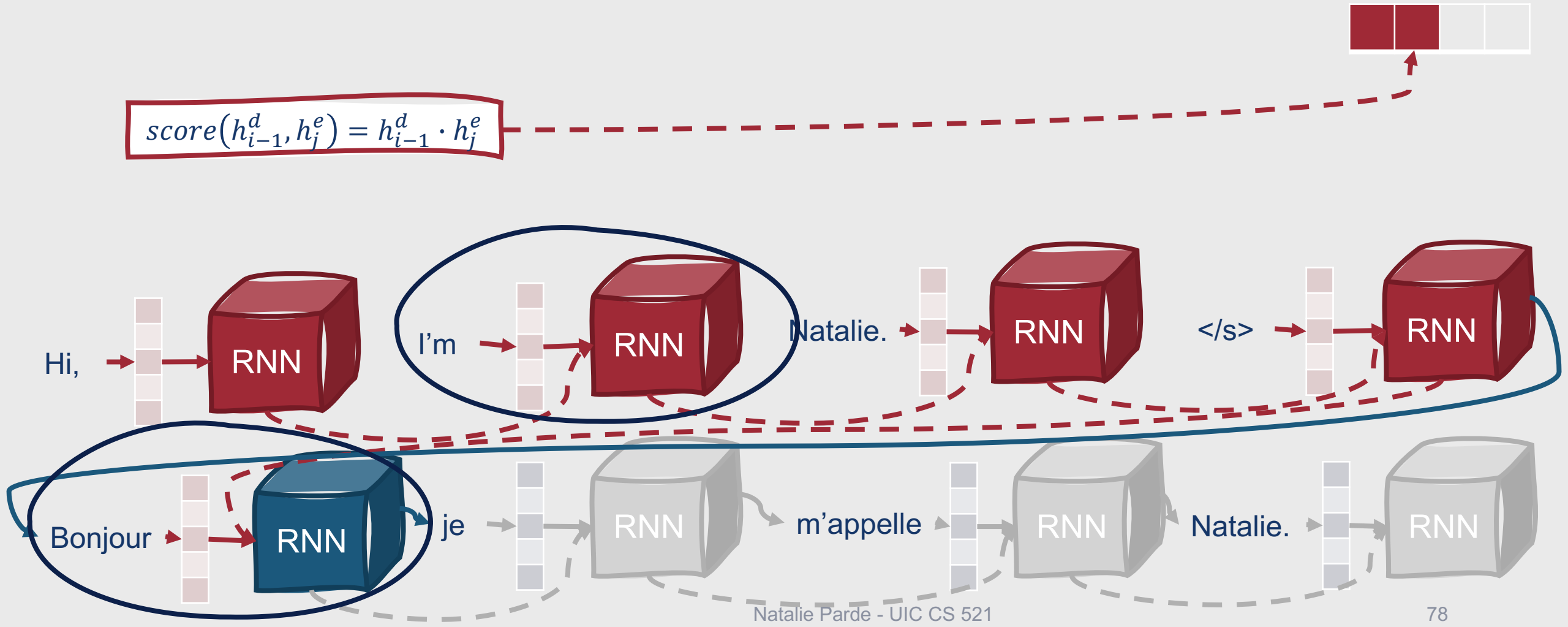
# Vector of Context Scores



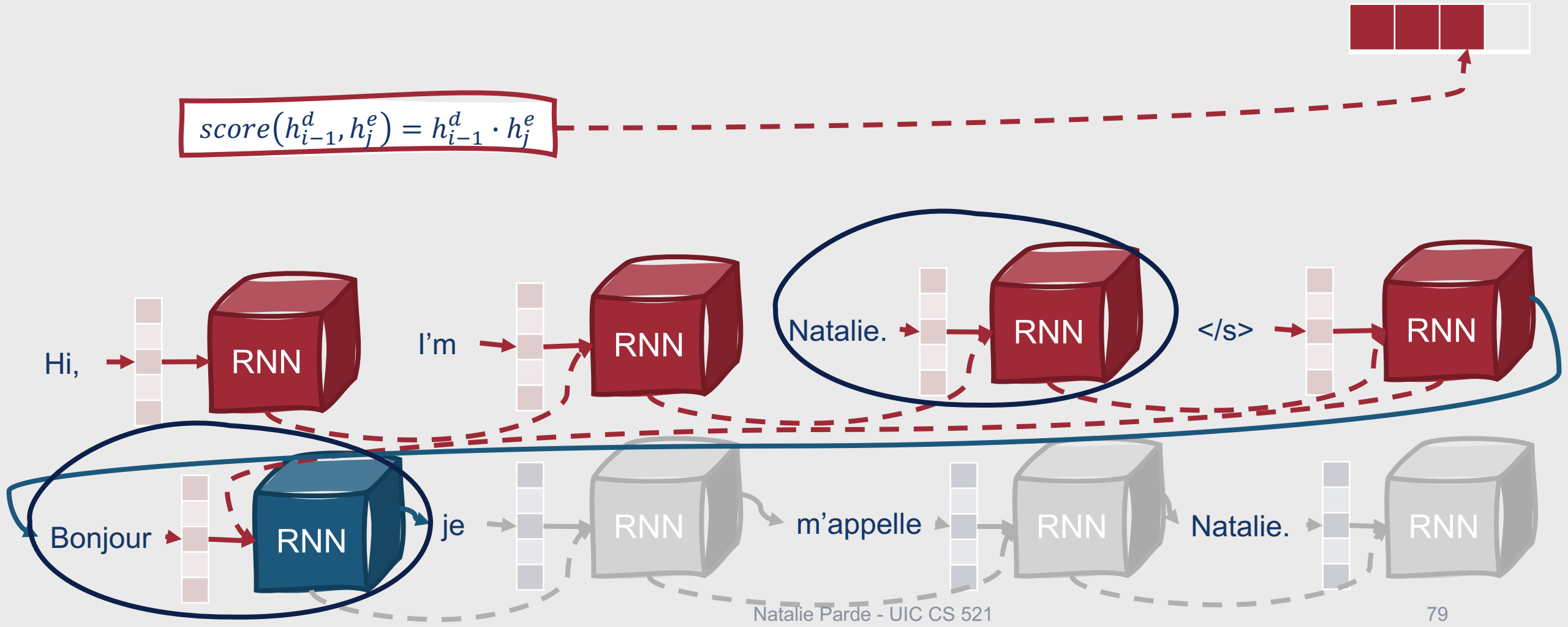
# Vector of Context Scores



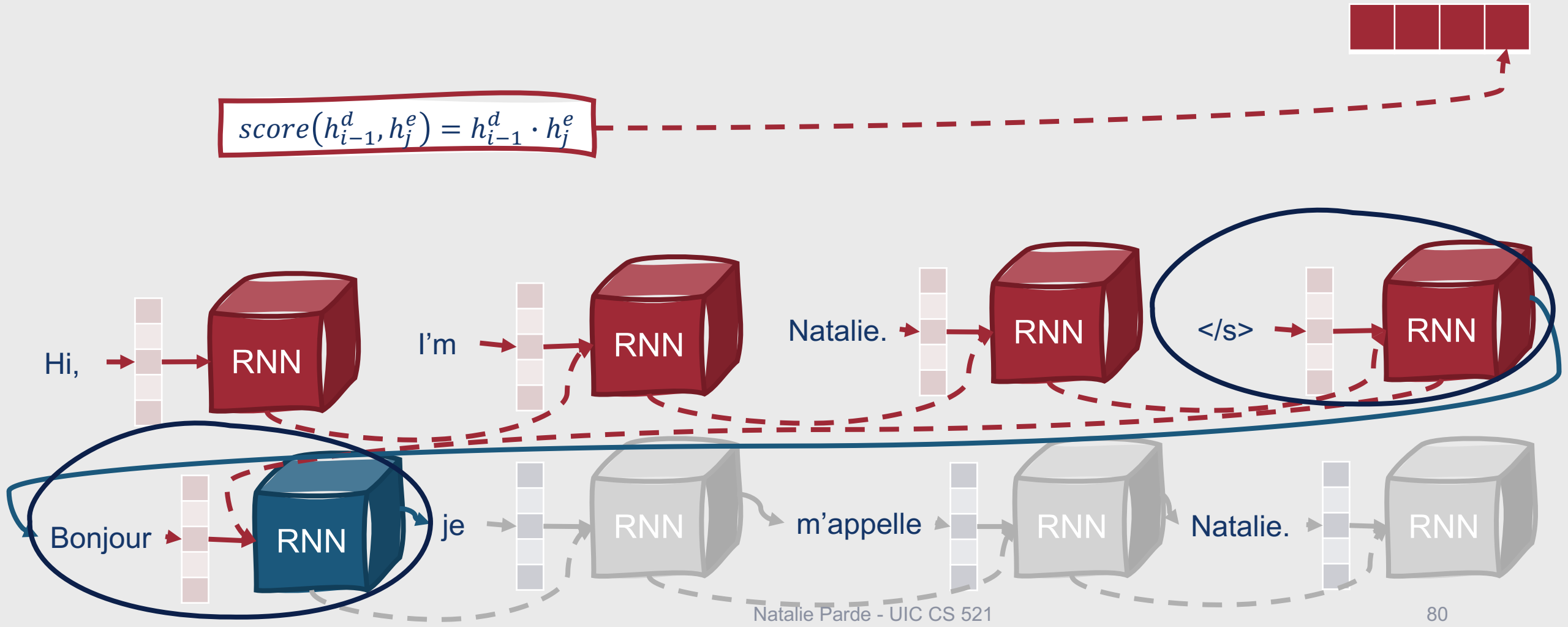
# Vector of Context Scores



# Vector of Context Scores



# Vector of Context Scores



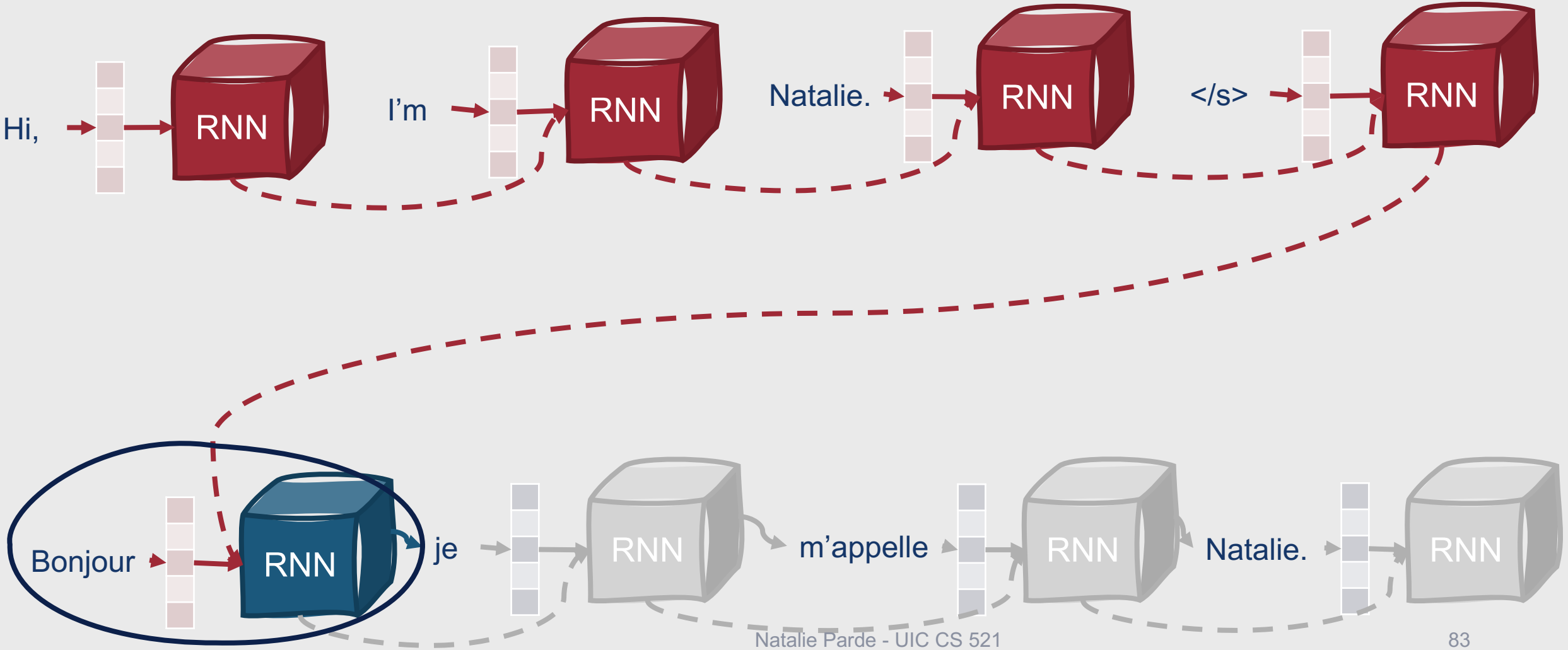
# How can we make use of context scores?

- Parameterize these scores with weights
- This allows the model to learn which aspects of similarity between the encoder and decoder states are important

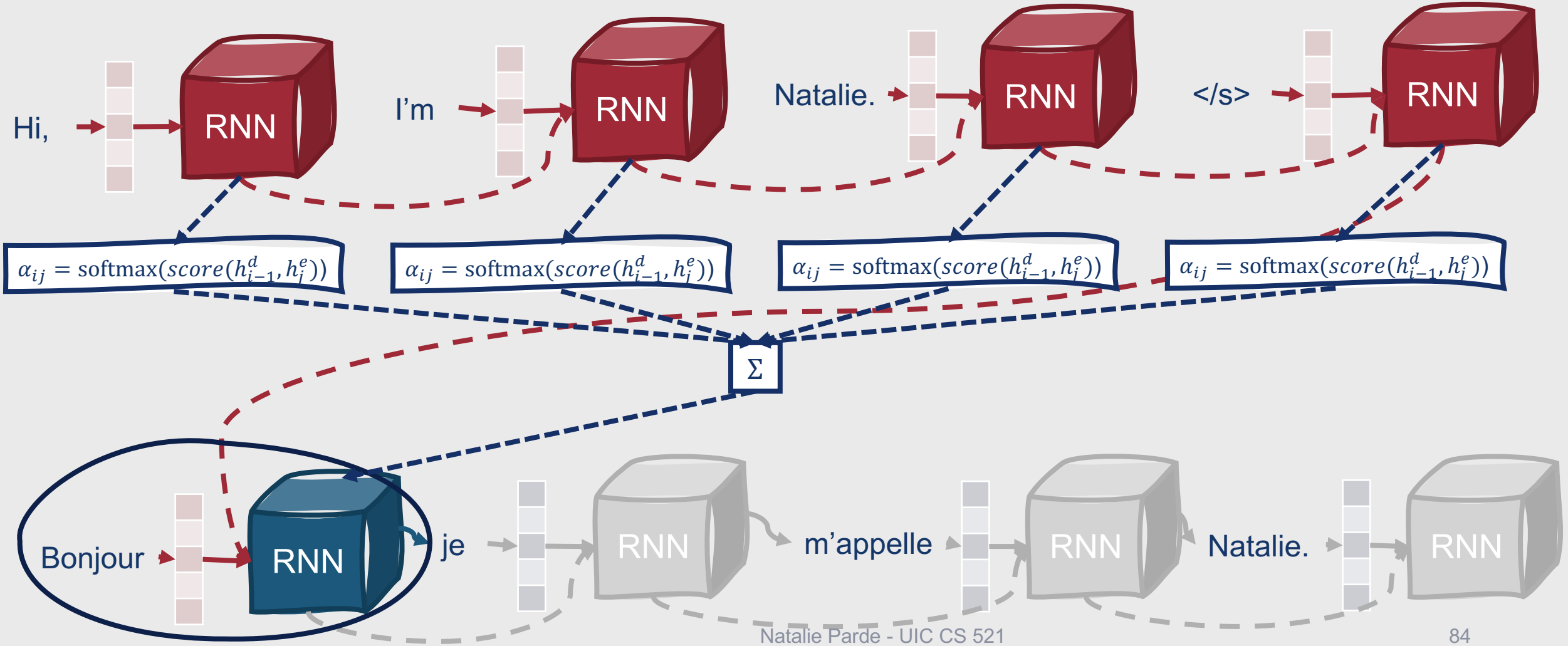
# Attention Weights

- **Normalize context scores** to create a vector of weights, $\alpha_{ij}$
  - $\alpha_{ij} = \text{softmax}(score(h_{i-1}^{d}, h_{j}^{e}) \forall j \in e)$
  - Provides the proportional relevance of each encoder hidden state $j$ to the current decoder state $i$
- Finally, **take a weighted average over all the encoder hidden states** to create a fixed-length context vector for the current decoder state
  - $c_i = \sum_j \alpha_{ij} h_j^e$

# Thus, we finally have an encoder-decoder model with attention!



# Thus, we finally have an encoder-decoder model with attention!

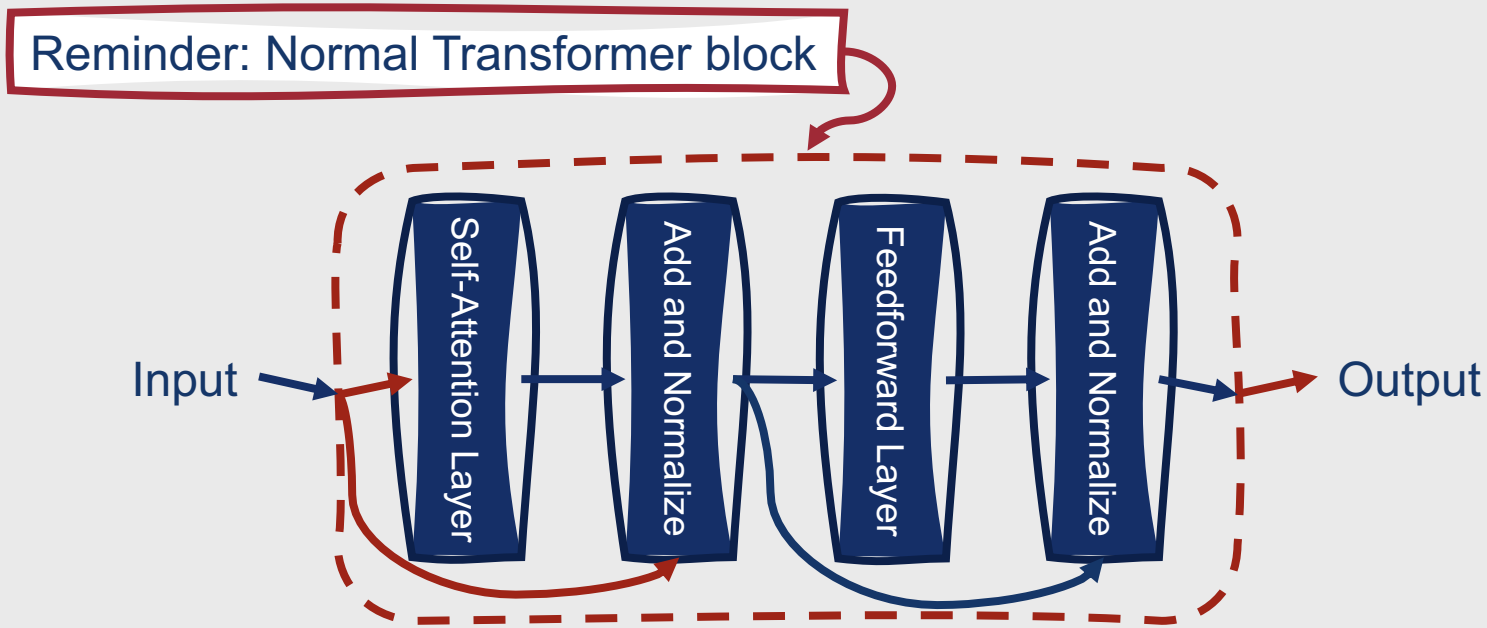


# Other Attention Weights

- More sophisticated scoring functions can be used as well
- Common: Parameterize the attention score with its own set of trainable weights
  - $\text{score}\left(\mathbf{h}_{i-1}^{d}, \mathbf{h}_{j}^{e}\right) = \mathbf{h}_{t-1}^{d}\mathbf{W}_{s}\mathbf{h}_{j}^{e}$
  - Advantage: Allows the encoder and decoder to use vectors with different dimensionality (dot-product attention requires the encoder and decoder hidden states to have the same dimensionality)

# Encoder-Decoder Models with Transformers

- Similar to other encoder-decoder models
  - Encoder (Transformer model) maps sequential input to an output representation
  - Decoder (Transformer model) attends to the encoder representation and generates sequential output autoregressively
- However….
  - Transformer blocks in the decoder include an extra **cross-attention** layer




# Cross-Attention

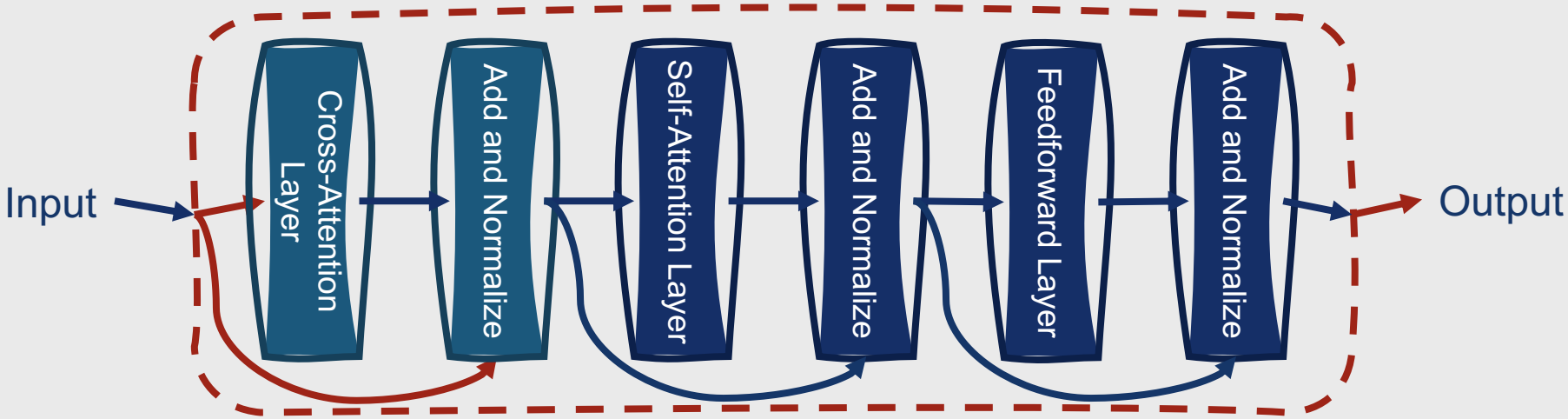
- Same form as **multiheaded self-attention** in a normal Transformer block, with one difference: queries come from the previous layer of the decoder as usual, but **keys and values come from the output of the encoder**
- Multihead attention:
  - Split key, query, and value parameters *n* ways
  - Pass each split independently through a separate attention head
  - Combine attention calculations from each head to produce a final attention score

# Cross-Attention

- $\mathbf{Q} = \mathbf{W}^{\mathbf{Q}}\mathbf{H}^{dec[i-1]}$
- $\mathbf{K} = \mathbf{W}^{\mathbf{Q}}\mathbf{H}^{enc}$
- $\mathbf{V} = \mathbf{W}^{\mathbf{V}}\mathbf{H}^{enc}$

- $CrossAttention(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^{\mathbf{T}}}{\sqrt{d_k}}\right)\mathbf{V}$

# Updated Decoder Transformer Block



# Encoder-Decoder Models with Transformers

- Why is cross-attention useful?
  - Allows the decoder to attend to the entire source language text
- Training Transformer-based encoder-decoders is similar to training RNN-based encoder-decoders
  - Use teacher forcing
  - Train autoregressively

# Practical Details for Building MT Systems

## Vocabulary

- MT systems typically use a fixed vocabulary generated using byte pair encoding or other wordpiece algorithms
- Vocabulary is usually shared across the source and target languages

## Corpora

- Parallel corpora with the same content communicated in multiple languages
- Common sources:
  - Government documents for nations with multiple official languages
  - Subtitles for movies and TV shows
- Often, text from the source and target language(s) is aligned at the sentence level

# What if we don't have much training data?

- Parallel corpora are difficult to find, especially for lower-resource language pairs
- **Backtranslation:**
  1. Train an intermediate target-to-source MT system on a small parallel corpus
  2. Translate additional monolingual data from the target language to the source language using this intermediate system
  3. Consider this new, synthetic parallel data as additional training data
  4. Train a source-to-target MT system on the expanded training dataset

# How do we evaluate machine translation models?

- Translation quality tends to be very subjective!
- Two common approaches:
  - **Human ratings**
  - **Automated metrics**

# Evaluating Machine Translation Using Human Ratings

- Typically evaluated along multiple dimensions
- Tend to check for both **fluency** and **adequacy**
- **Fluency:**
  - Clarity
  - Naturalness
  - Style
- **Adequacy:**
  - Fidelity
  - Informativeness

# Evaluating Machine Translation Using Human Ratings

- How to get quantitative measures of fluency?
  - Ask humans to rate different aspects of fluency along a scale
  - Measure how long it takes humans to read a segment of text
  - Ask humans to guess the identity of the missing word
    - “After such a late night working on my project, it was hard to wake up this _____!”

# Evaluating Machine Translation Using Human Ratings

- How to get quantitative measures of adequacy?
  - Ask bilingual raters to rate how much information was preserved in the translation
  - Ask monolingual raters to do the same, given access to a gold standard reference translation
  - Ask humans to answer multiple-choice questions about content present in a translation

# Another set of human evaluation metrics considers post-editing.

- Ask a human to **post-edit** or “fix” a translation
- Compute the number of edits required to correct the output to an acceptable level
  - Can be measured via number of word changes, number of keystrokes, amount of time taken, etc.

# Automated Metrics

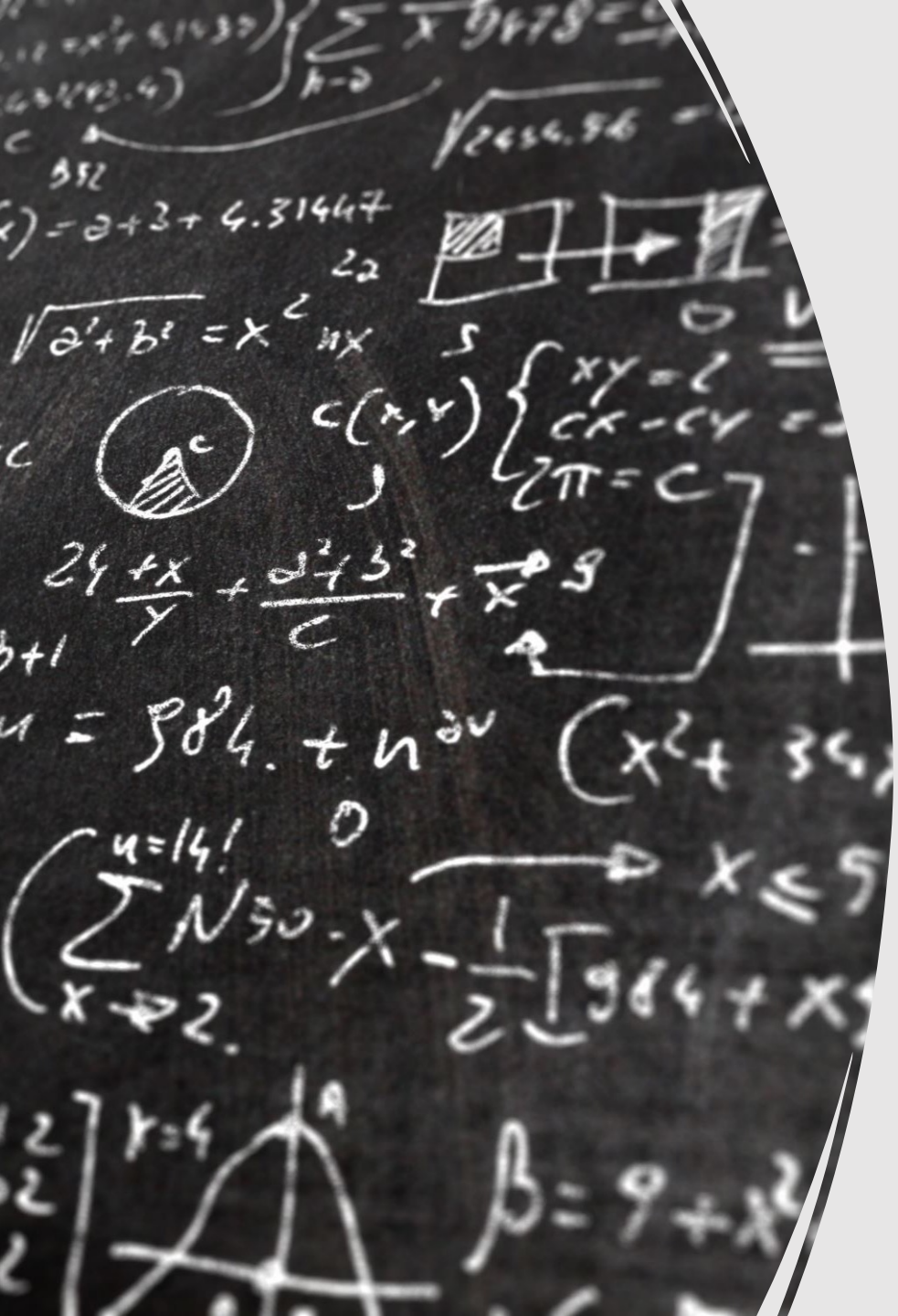
- Less accurate than human evaluation, but:
  - Useful for iteratively testing system improvements
  - Can be used as an automatic loss function
- Two main families:
  - Character- or word-overlap
  - Embedding similarity

# Popular Lexical Overlap Metrics

- **BLEU**
  - Measure of word overlap
- **METEOR**
  - Measure of word overlap, considering stemming and synonymy
- **Character F-Score (chrF)**
  - Measure of character n-gram overlap

# BLEU

- Weighted average of the number of n-gram overlaps with human translations
- **Precision-based metric**
  - What percentage of words in the candidate translation also occur in the gold standard translation(s)?



# How is BLEU computed?

- Count the maximum number of times each n-gram is used in any single reference translation, $c_{max}(\text{n}-\text{gram})$
- Count the number of times each n-gram is used in the candidate translation
- Clip that amount so that the highest it can be is $c_{max}(\text{n}-\text{gram})$
- Compute precision for each word in the candidate translation based on that clipped amount
  - $\text{prec}_n = \frac{\Sigma_{c\in\{\text{Candidates}\}} \Sigma_{\text{n}-\text{gram}\in C} \min(c(\text{n}-\text{gram}), c_{max}(\text{n}-\text{gram}))}{\Sigma_{c\in\{\text{Candidates}\}} \Sigma_{\text{n}-\text{gram}\in C} c(\text{n}-\text{gram})}$
- Take the geometric mean of the modified n-gram precisions for unigrams, bigrams, trigrams, and 4-grams

# BLEU also adds a penalty for translation brevity.

- Otherwise, extremely short translations (e.g., “the”) could receive perfect scores!
- The penalty is based on two values:
  - The effective reference length, *r*, for the corpus
    - The sum of the lengths of the best matches for each candidate sentence
  - The total length of the candidate translation corpus, *c*
- Formally, the penalty is set to:
  - $BP = \begin{cases} 1 & if\ c > r \\ e^{(1-\frac{r}{c})} & if\ c \leq r \end{cases}$

# Computing BLEU

- The full BLEU score for a set of translations is then:
  - $BLEU = BP * (\prod_{n=1}^{4} \text{prec}_n)^{\frac{1}{4}}$

# Example: Computing BLEU

Natalie no dió una bofetada a la bruja verde. Source Sentence

Natalie didn’t slap the green witch. Reference Translation

Natalie did not give a slap to the green witch. Candidate Translation

# Example: Computing BLEU

Natalie no dió una bofetada a la bruja verde. Source Sentence

Natalie didn't slap the green witch. Reference Translation

Natalie did not give a slap to the green witch. Candidate Translation

$$\text{prec}_n = \frac{\sum_{c \in \{\text{Candidates}\}} \sum_{\text{n-gram} \in C} \min(\text{c(n-gram)}, \text{c}_{\max}\text{(n-gram)})}{\sum_{c \in \{\text{Candidates}\}} \sum_{\text{n-gram} \in C} \text{c(n-gram)}}$$

$$BP = \begin{cases} 1 & if\ c > r \\ e^{(1-\frac{r}{c})} & if\ c \leq r \end{cases}$$

$$BLEU = BP * (\prod_{n=1}^{4} \text{prec}_n)^{\frac{1}{4}}$$

# Example: Computing BLEU

Natalie didn't slap the green witch.

Natalie did not give a slap to the green witch.

$$\text{prec}_n = \frac{\sum_{c \in \{\text{Candidates}\}} \sum_{\text{n-gram} \in C} \min(\text{c(n-gram)}, \text{c}_{\max}\text{(n-gram)})}{\sum_{c \in \{\text{Candidates}\}} \sum_{\text{n-gram} \in C} \text{c(n-gram)}}$$

$$BP = \begin{cases} 1 & if\ c > r \\ e^{(1-\frac{r}{c})} & if\ c \leq r \end{cases}$$

$$BLEU = BP * (\prod_{n=1}^{4} \text{prec}_n)^{\frac{1}{4}}$$

| Unigram | Unigram Frequency (Candidate) | Unigram Frequency (Reference) |
|---|---|---|
| Natalie | 1 | 1 |
| did | 1 | 0 |
| not | 1 | 0 |
| give | 1 | 0 |
| a | 1 | 0 |
| slap | 1 | 1 |
| to | 1 | 0 |
| the | 1 | 1 |
| green | 1 | 1 |
| witch | 1 | 1 |
| . | 1 | 1 |

# Example: Computing BLEU

Natalie didn't slap the green witch.

Natalie did not give a slap to the green witch.

$$\text{prec}_n = \frac{\sum_{c \in \{\text{Candidates}\}} \sum_{\text{n-gram} \in C} \min(\text{c(n-gram)}, \text{c}_{\max}\text{(n-gram)})}{\sum_{c \in \{\text{Candidates}\}} \sum_{\text{n-gram} \in C} \text{c(n-gram)}}$$

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| a | 1 | 0 |
| slap | 1 | 1 |
| to | 1 | 0 |
| the | 1 | 1 |
| green | 1 | 1 |
| witch | 1 | 1 |
| . | 1 | 1 |

$$p_1 = \frac{1+0+0+0+0+1+0+1+1+1+1}{1+1+1+1+1+1+1+1+1+1+1} = \frac{6}{11}$$

# Example: Computing BLEU

Natalie didn't slap the green witch.

Natalie did not give a slap to the green witch.

$$\text{prec}_n = \frac{\sum_{c \in \{\text{Candidates}\}} \sum_{\text{n-gram} \in C} \min(\text{c(n-gram)}, \text{c}_{\max}\text{(n-gram)})}{\sum_{c \in \{\text{Candidates}\}} \sum_{\text{n-gram} \in C} \text{c(n-gram)}}$$

$$BP = \begin{cases} 1 & if\ c > r \\ e^{(1-\frac{r}{c})} & if\ c \leq r \end{cases}$$

$$BLEU = BP * (\prod_{n=1}^{4} \text{prec}_n)^{\frac{1}{4}}$$

| Bigram | Bigram Frequency (Candidate) | Bigram Frequency (Reference) |
|---|---|---|
| Natalie did | 1 | 0 |
| did not | 1 | 0 |
| not give | 1 | 0 |
| give a | 1 | 0 |
| a slap | 1 | 0 |
| slap to | 1 | 0 |
| to the | 1 | 0 |
| the green | 1 | 1 |
| green witch | 1 | 1 |
| witch . | 1 | 1 |

$$p_1 = \frac{1+0+0+0+0+1+0+1+1+1+1}{1+1+1+1+1+1+1+1+1+1+1} = \frac{6}{11}$$

$$p_2 = \frac{0+0+0+0+0+0+0+1+1+1}{1+1+1+1+1+1+1+1+1+1} = \frac{3}{10}$$

# Example: Computing BLEU

Natalie didn't slap the green witch.

Natalie did not give a slap to the green witch.

$$\text{prec}_n = \frac{\sum_{c \in \{\text{Candidates}\}} \sum_{\text{n-gram} \in C} \min(\text{c(n-gram)}, \text{c}_{\max}\text{(n-gram)})}{\sum_{c \in \{\text{Candidates}\}} \sum_{\text{n-gram} \in C} \text{c(n-gram)}}$$

$$BP = \begin{cases} 1 & if\ c > r \\ e^{(1-\frac{r}{c})} & if\ c \leq r \end{cases}$$

| Trigram | Trigram Frequency (Candidate) | Trigram Frequency (Reference) |
|---|---|---|
| Natalie did not | 1 | 0 |
| did not give | 1 | 0 |
| not give a | 1 | 0 |
| give a slap | 1 | 0 |
| a slap to | 1 | 0 |
| slap to the | 1 | 0 |
| to the green | 1 | 0 |
| the green witch | 1 | 1 |
| green witch . | 1 | 1 |

$$BLEU = BP * (\prod_{n=1}^{4} \text{prec}_n)^{\frac{1}{4}}$$

$$p_1 = \frac{6}{11} \qquad p_2 = \frac{3}{10}$$

$$p_3 = \frac{0+0+0+0+0+0+0+1+1}{1+1+1+1+1+1+1+1+1} = \frac{2}{9}$$

# Example: Computing BLEU

Natalie didn't slap the green witch.

Natalie did not give a slap to the green witch.

$$\text{prec}_n = \frac{\sum_{c \in \{\text{Candidates}\}} \sum_{\text{n-gram} \in C} \min(\text{c(n-gram)}, \text{c}_{\max}\text{(n-gram)})}{\sum_{c \in \{\text{Candidates}\}} \sum_{\text{n-gram} \in C} \text{c(n-gram)}}$$

$$BP = \begin{cases} 1 & if\ c > r \\ e^{(1-\frac{r}{c})} & if\ c \leq r \end{cases}$$

| 4-gram | 4-gram Frequency (Candidate) | 4-gram Frequency (Reference) |
|---|---|---|
| Natalie did not give | 1 | 0 |
| did not give a | 1 | 0 |
| not give a slap | 1 | 0 |
| give a slap to | 1 | 0 |
| a slap to the | 1 | 0 |
| slap to the green | 1 | 0 |
| to the green witch | 1 | 0 |
| the green witch . | 1 | 1 |

$$BLEU = BP * (\prod_{n=1}^{4} \text{prec}_n)^{\frac{1}{4}}$$

$$p_1 = \frac{6}{11} \qquad p_2 = \frac{3}{10} \qquad p_3 = \frac{2}{9}$$

$$p_4 = \frac{0+0+0+0+0+0+0+1}{1+1+1+1+1+1+1+1} = \frac{1}{8}$$

# Example: Computing BLEU

Natalie didn't slap the green witch.

Natalie did not give a slap to the green witch.

c = 11

r = 7

$$\text{prec}_n = \frac{\sum_{c \in \{\text{Candidates}\}} \sum_{\text{n-gram} \in C} \min(\text{c(n-gram)}, \text{c}_{\max}\text{(n-gram)})}{\sum_{c \in \{\text{Candidates}\}} \sum_{\text{n-gram} \in C} \text{c(n-gram)}}$$

$$BP = \begin{cases} 1 & if\ c > r \\ e^{(1-\frac{r}{c})} & if\ c \leq r \end{cases}$$

$$BLEU = BP * (\prod_{n=1}^{4} \text{prec}_n)^{\frac{1}{4}}$$

$$p_1 = \frac{6}{11} \quad p_2 = \frac{3}{10} \quad p_3 = \frac{2}{9} \quad p_4 = \frac{1}{8}$$

$$BP = 1$$

$$BLEU = 1 * (\prod_{n=1}^{4} \text{prec}_n)^{\frac{1}{4}} = 1 * (\frac{6}{11} * \frac{3}{10} * \frac{2}{9} * \frac{1}{8})^{\frac{1}{4}} = 1 * 0.00454545454^{\frac{1}{4}} = 1 * 0.25965358893 = 0.26$$

# Limitations of BLEU

- Word or phrase order is of minimal importance
  - When computing unigram precision, a word can exist anywhere in the translation!
- Does not consider word similarity
- Relatively low correlation with human ratings
- Nonetheless, BLEU is reasonable to use in cases when a quick, automated metric is needed to assess translation performance

# Character F-Score (chrF)

- Same intuition as BLEU: Good machine translations tend to contain the same words and characters as human translations
- Ranks a candidate translation by a function of the number of character n-gram overlaps with a human reference translation
- Less sensitive to word tokenization than BLEU

# How is chrF computed?

- Similarly to "regular" F-score
  - **chrP:** averaged % of character unigrams, bigrams, …, k-grams in the hypothesis that also occur in the reference
  - **chrR:** averaged % of character unigrams, bigrams, …, k-grams in the reference that also occur in the hypothesis
  - **β:** weighting parameter (similarly to F-score) that determines the relative impacts of chrP and chrR on the overall F-score
  - $\text{chrF}\beta = (1+\beta^2)\frac{\text{chrP}\times\text{chrR}}{\beta^2\times\text{chrP}+\text{chrR}}$, or $\text{chrF2} = \frac{5\times\text{chrP}\times\text{chrR}}{4\times\text{chrP}+\text{chrR}}$

# Example: Computing chrF

# Example: Computing chrF


# Example: Computing chrF



| C | S | 5 | 2 | 1 | i | s | t | h | e | b | e | s | t |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|

| C | S | 5 | 2 | 1 | i | s | g | r | e | a | t |
|---|---|---|---|---|---|---|---|---|---|---|---|

# Example: Computing chrF



| C | S | 5 | 2 | 1 | i | s | t | h | e | b | e | s | t |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|

14 unigrams, 13 bigrams

| C | S | 5 | 2 | 1 | i | s | g | r | e | a | t |
|---|---|---|---|---|---|---|---|---|---|---|---|

12 unigrams, 11 bigrams

# Example: Computing chrF



| C | S | 5 | 2 | 1 | i | s | t | h | e | b | e | s | t |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|

← 14 unigrams, 13 bigrams

| C | S | 5 | 2 | 1 | i | s | g | r | e | a | t |
|---|---|---|---|---|---|---|---|---|---|---|---|

← 12 unigrams, 11 bigrams

**chrP:** averaged % of character unigrams, bigrams, …, k-grams in the hypothesis that are also in the reference

k=3

**chrR:** averaged % of character unigrams, bigrams, …, k-grams in the reference that are also in the hypothesis

# Example: Computing chrF



| C | S | 5 | 2 | 1 | i | s | t | h | e | b | e | s | t |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|

14 unigrams, 13 bigrams

| C | S | 5 | 2 | 1 | i | s | g | r | e | a | t |
|---|---|---|---|---|---|---|---|---|---|---|---|

12 unigrams, 11 bigrams

**chrP:** averaged % of character unigrams, bigrams, …, k-grams in the hypothesis that are also in the reference

**chrR:** averaged % of character unigrams, bigrams, …, k-grams in the reference that are also in the hypothesis

k=3

9 unigrams are in both the hypothesis and the reference

# Example: Computing chrF



| CS | S5 | 52 | 21 | 1i | is | st | th | he | eb | be | es | st |
|---|---|---|---|---|---|---|---|---|---|---|---|---|

← 14 unigrams, 13 bigrams

| CS | S5 | 52 | 21 | 1i | is | sg | gr | re | ea | at |
|---|---|---|---|---|---|---|---|---|---|---|

← 12 unigrams, 11 bigrams

**chrP:** averaged % of character unigrams, bigrams, …, k-grams in the hypothesis are also in the reference

**chrR:** averaged % of character unigrams, bigrams, …, k-grams in the reference that are also in the hypothesis

k=3

9 unigrams are in both the hypothesis and the reference

6 bigrams are in both the hypothesis and the reference

# Example: Computing chrF



| CS5 | S52 | 521 | 21i | 1is | ist | sth | the | heb | ebe | bes | est |
|---|---|---|---|---|---|---|---|---|---|---|---|

← 14 unigrams, 13 bigrams

| CS5 | S52 | 521 | 21i | 1is | isg | sgr | gre | rea | eat |
|---|---|---|---|---|---|---|---|---|---|

← 12 unigrams, 11 bigrams

**chrP:** averaged % of character unigrams, bigrams, …, k-grams in the hypothesis that are also in the reference

**chrR:** averaged % of character unigrams, bigrams, …, k-grams in the reference that are also in the hypothesis

k=3

9 unigrams are in both the hypothesis and the reference

6 bigrams are in both the hypothesis and the reference

5 trigrams are in both the hypothesis and the reference

# Example: Computing chrF



| CS5 | S52 | 521 | 21i | 1is | ist | sth | the | heb | ebe | bes | est |
|---|---|---|---|---|---|---|---|---|---|---|---|

← 14 unigrams, 13 bigrams

| CS5 | S52 | 521 | 21i | 1is | isg | sgr | gre | rea | eat |
|---|---|---|---|---|---|---|---|---|---|

← 12 unigrams, 11 bigrams

**chrP:** averaged % of character unigrams, bigrams, …, k-grams in the hypothesis that are also in the reference

**chrR:** averaged % of character unigrams, bigrams, …, k-grams in the reference that are also in the hypothesis

k=3

9 unigrams are in both the hypothesis and the reference

Unigram chrP: $^{9}/_{12} = 0.75$

Unigram chrR: $^{9}/_{14} = 0.64$

6 bigrams are in both the hypothesis and the reference

5 trigrams are in both the hypothesis and the reference

# Example: Computing chrF



| CS5 | S52 | 521 | 21i | 1is | ist | sth | the | heb | ebe | bes | est |
|---|---|---|---|---|---|---|---|---|---|---|---|

← 14 unigrams, 13 bigrams

| CS5 | S52 | 521 | 21i | 1is | isg | sgr | gre | rea | eat |
|---|---|---|---|---|---|---|---|---|---|

← 12 unigrams, 11 bigrams

**chrP:** averaged % of character unigrams, bigrams, …, k-grams in the hypothesis that are also in the reference

**chrR:** averaged % of character unigrams, bigrams, …, k-grams in the reference that are also in the hypothesis

k=3

9 unigrams are in both the hypothesis and the reference

6 bigrams are in both the hypothesis and the reference

5 trigrams are in both the hypothesis and the reference

Unigram chrP: $^{9}/_{12} = 0.75$

Unigram chrR: $^{9}/_{14} = 0.64$

Bigram chrP: $^{6}/_{11} = 0.55$

Bigram chrR: $^{6}/_{13} = 0.46$

# Example: Computing chrF

CS 521 is the best 

CS 521 is great 

| CS5 | S52 | 521 | 21i | 1is | ist | sth | the | heb | ebe | bes | est |
|---|---|---|---|---|---|---|---|---|---|---|---|

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Bigram chrR: $^{6}/_{13} = 0.46$

5 trigrams are in both the hypothesis and the reference

Trigram chrP: $^{5}/_{10} = 0.5$

Trigram chrR: $^{5}/_{12} = 0.42$

# Example: Computing chrF



| CS5 | S52 | 521 | 21i | 1is | ist | sth | the | heb | ebe | bes | est |
|---|---|---|---|---|---|---|---|---|---|---|---|

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chrP: $\frac{0.75+0.55+0.5}{3} = 0.6$

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Trigram chrR: $^{5}/_{12} = 0.42$

chrR: $\frac{0.64+0.46+0.42}{3} = 0.51$

# Example: Computing chrF



| CS5 | S52 | 521 | 21i | 1is | ist | sth | the | heb | ebe | bes | est |
|---|---|---|---|---|---|---|---|---|---|---|---|

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chrP: $\frac{0.75+0.55+0.5}{3} = 0.6$

chrR: $\frac{0.64+0.46+0.42}{3} = 0.51$

$$\text{chrF2} = \frac{5 * \text{chrP} * \text{chrR}}{4 * \text{chrP} + \text{chrR}} = \frac{5 * 0.6 * 0.51}{4 * 0.6 + 0.51} = 0.53$$

# Limitations of chrF

- Focuses on differences at a very local scale (i.e., character n-grams)
- Doesn’t measure discourse coherence
- Best at measuring performance for different versions of the same system, rather than comparing different systems

# Embedding-Based Evaluation Methods

- Measuring exact word- or character-level overlap might be overly strict
  - Good translations may use words that are synonymous to those in the reference!
- Embedding-based methods measure the *semantic* overlap between reference and hypothesis translations

# Popular Embedding-Based Methods for Evaluating MT Systems

## COMET

- https://github.com/Unbabel/COMET

## BLEURT

- https://github.com/google-research/bleurt

## BERTScore

- https://github.com/Tiiiger/bert_score

# Summary: Machine Translation and Encoder-Decoder Models

- There are many **typological differences** between languages that make translation a challenging task
- Classical approaches to machine translation focused on **dictionary-based methods**, **direct transfer** of source and target language parses, and logic-based **interlingua approaches**
- **Statistical approaches** bridged the gap between classical methods and modern neural MT
- Modern machine translation leverages **encoder-decoder models**, often generating candidate parses using **beam search**
- Encoder-decoder models often leverage **attention mechanisms** to improve the context passed from the encoder to the decoder
- MT systems are commonly evaluated using both **human ratings** and **automated metrics**
- Popular automated metrics include **BLEU**, **chrF**, and **embedding-based measures**