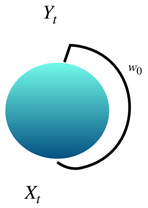
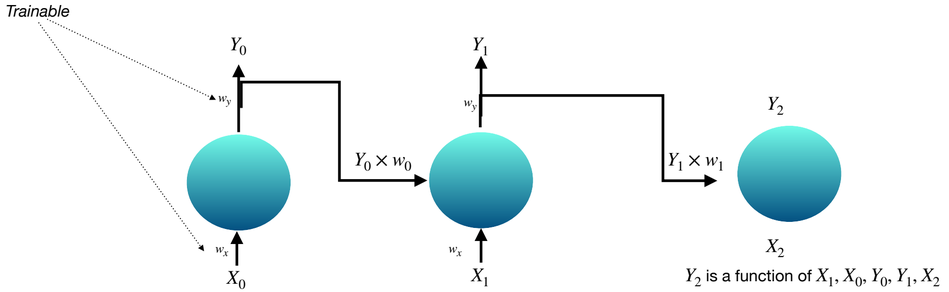
Stateless

Learns on random portions of text, without any information about the text

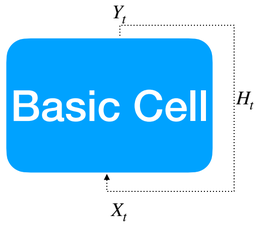
Stateful

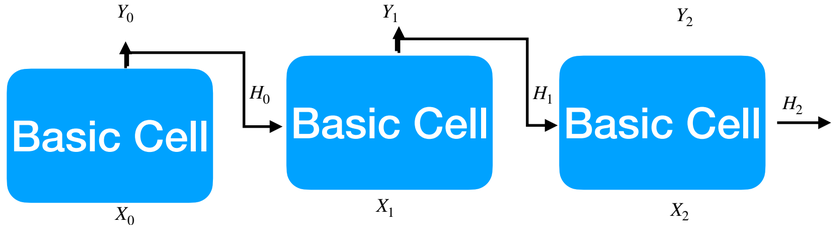
Learned hidden state preserved , allowing the model to learn longer patterns





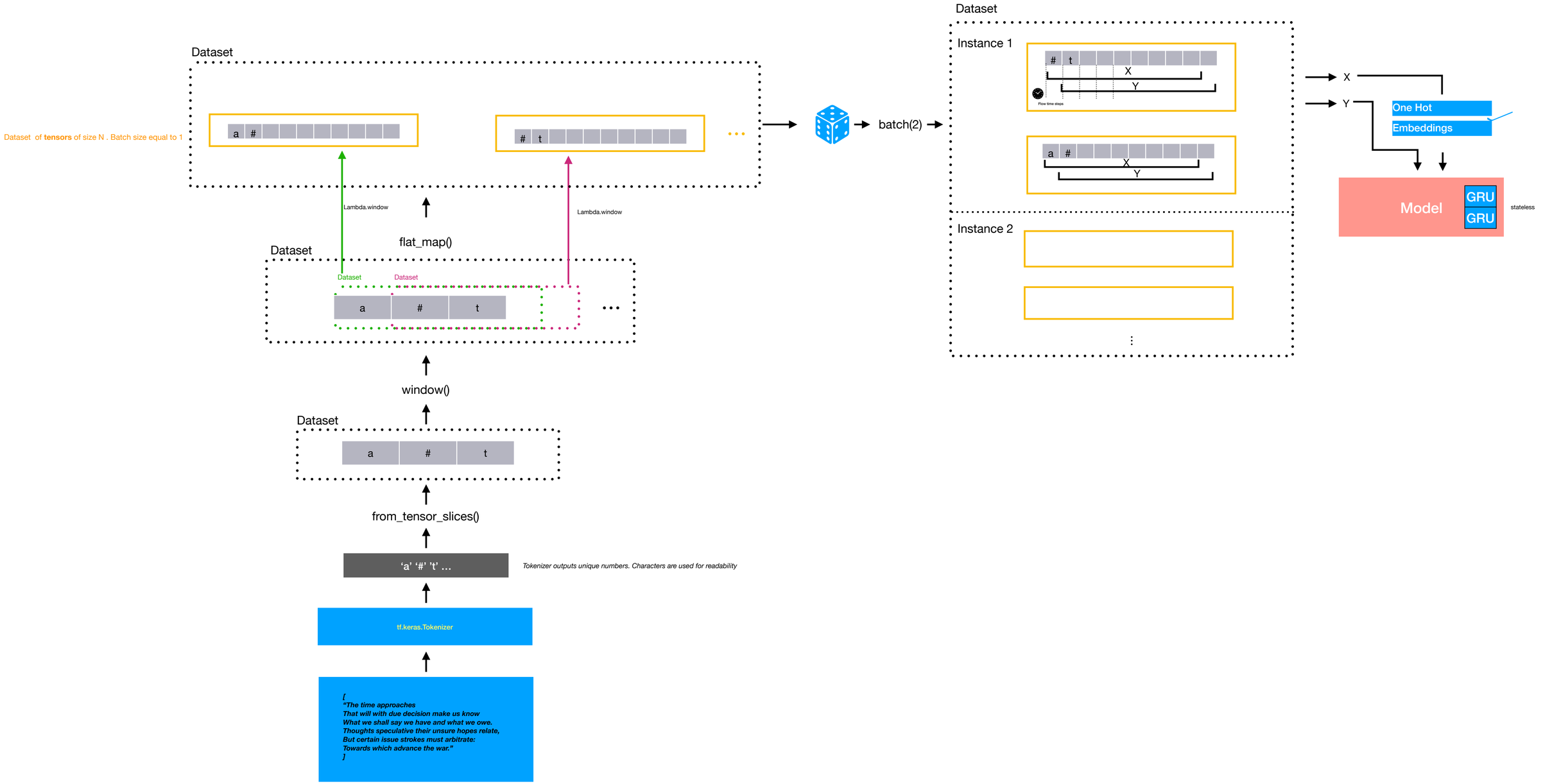
Y_2 is a function of X_1, X_0, Y_0, Y_1, X_2

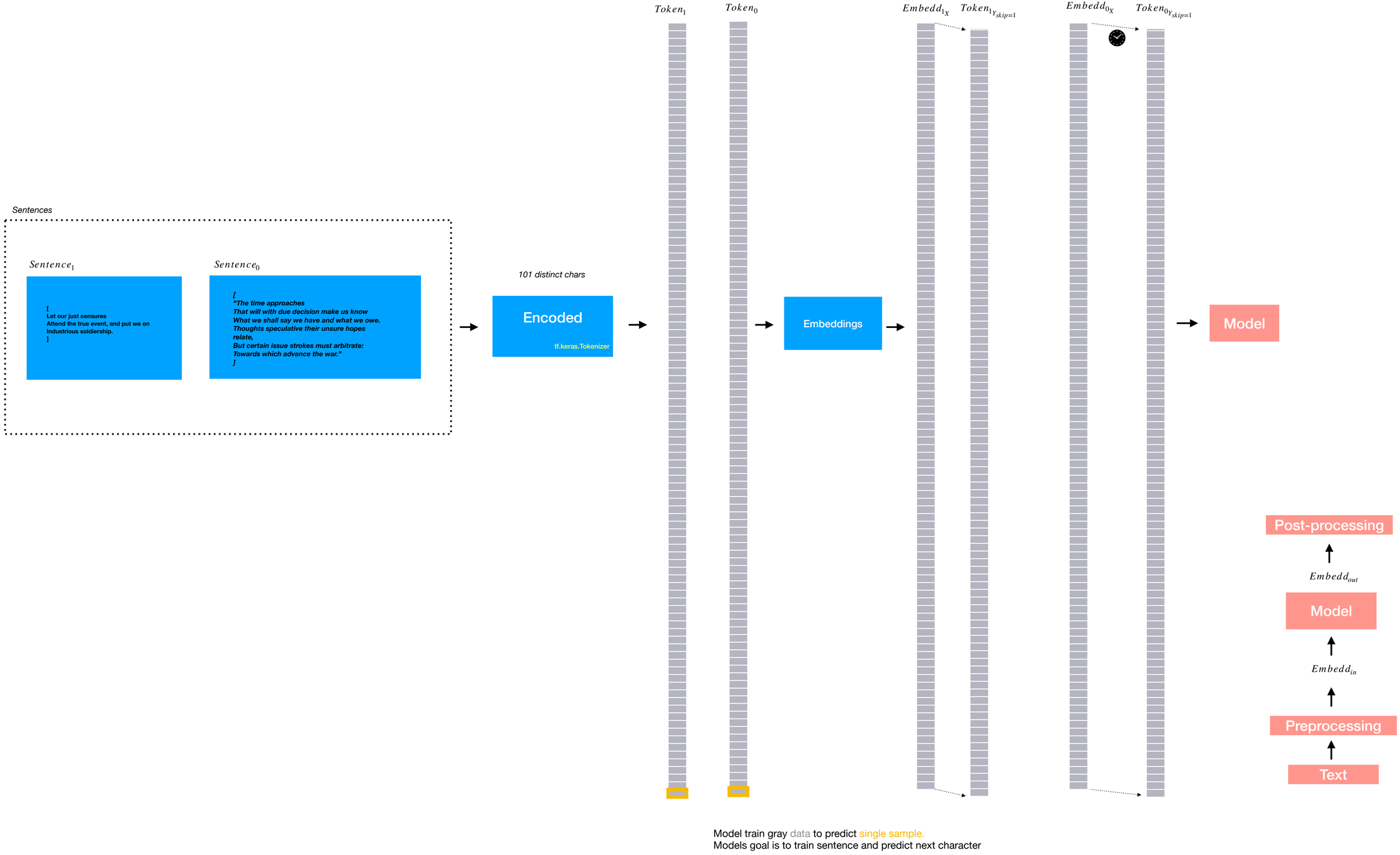




Y_2 is a function of H_1,X_2

H_2 is a function of H_1,$\tilde{X}_2$. $\tilde{X}_2$ is a weighted X_2

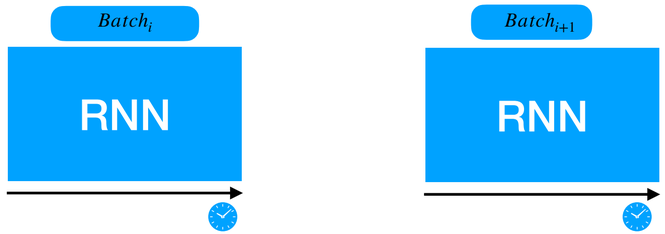

Dataset of tensors of size N . Batch size equal to 1
Dataset
a #
t
Lambda.window
Lambda.window
flat_map()
Dataset
Dataset
Dataset
a # t
window()
Dataset
a # t
from_tensor_slices()
'a' '#' 't' ...
Tokenizer outputs unique numbers. Characters are used for readability
tf.keras.Tokenizer
[
"The time approaches
That will with due decision make us know
What we shall say we have and what we owe.
Thoughts speculative their unsure hopes relate,
But certain issue strokes must arbitrate:
Towards which advance the war."
]
batch(2)
Dataset
Instance 1
t
X
Y
Flow time steps
a #
X
Y
Instance 2
X
Y
One Hot
Embeddings
Model
GRU
GRU
stateless



Model train gray data to predict single sample.
Models goal is to train sentence and predict next character

Stateless

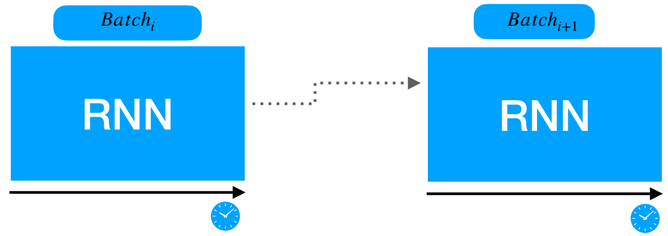
Learns on random portions of text, without any information about the text



Hidden state lost after each training iteration.

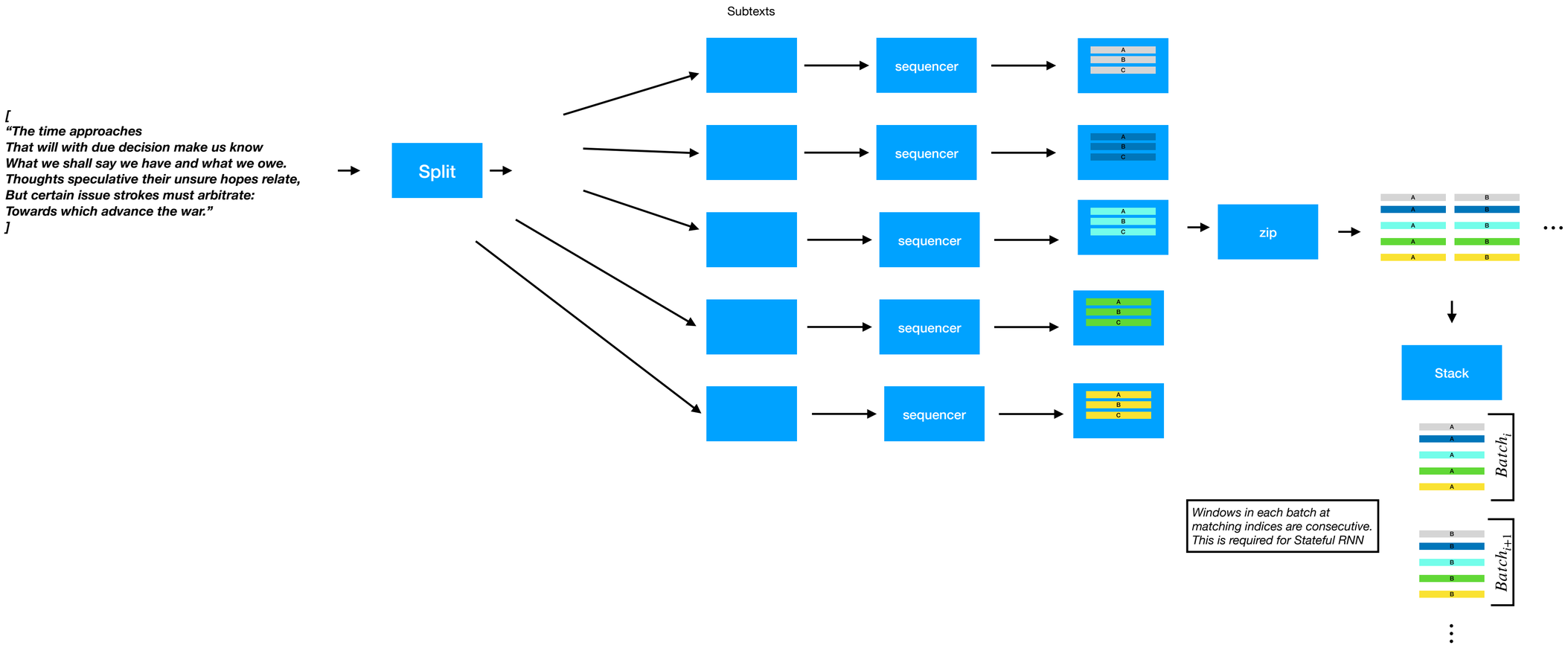
Stateful

Learned hidden state preserved , allowing the model to learn longer patterns



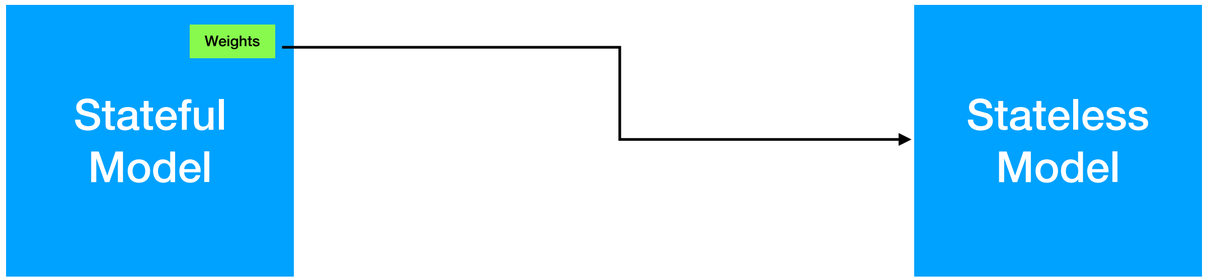
Preserve hidden state and using to train next batch

Batching: Stateful RNN



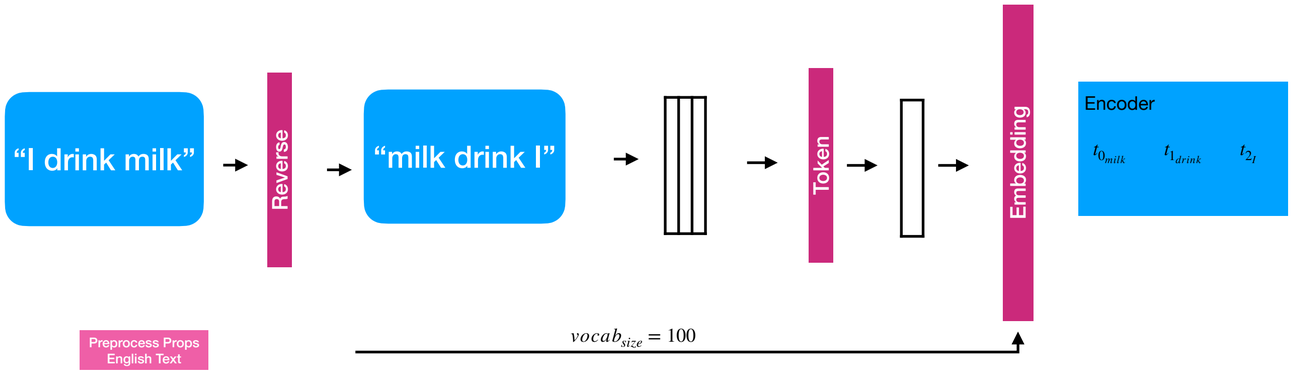
Batching: Stateful RNN

Batch size restricted to the training batch_size

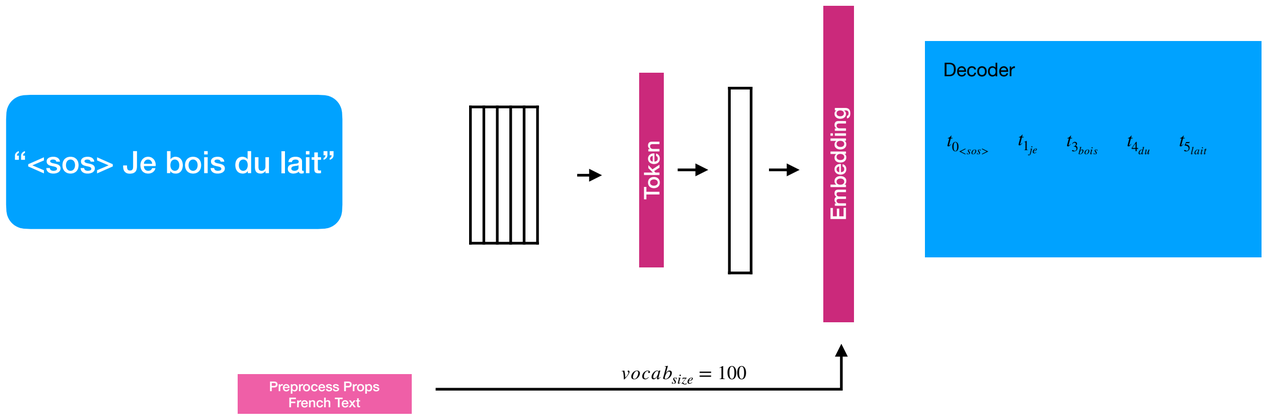


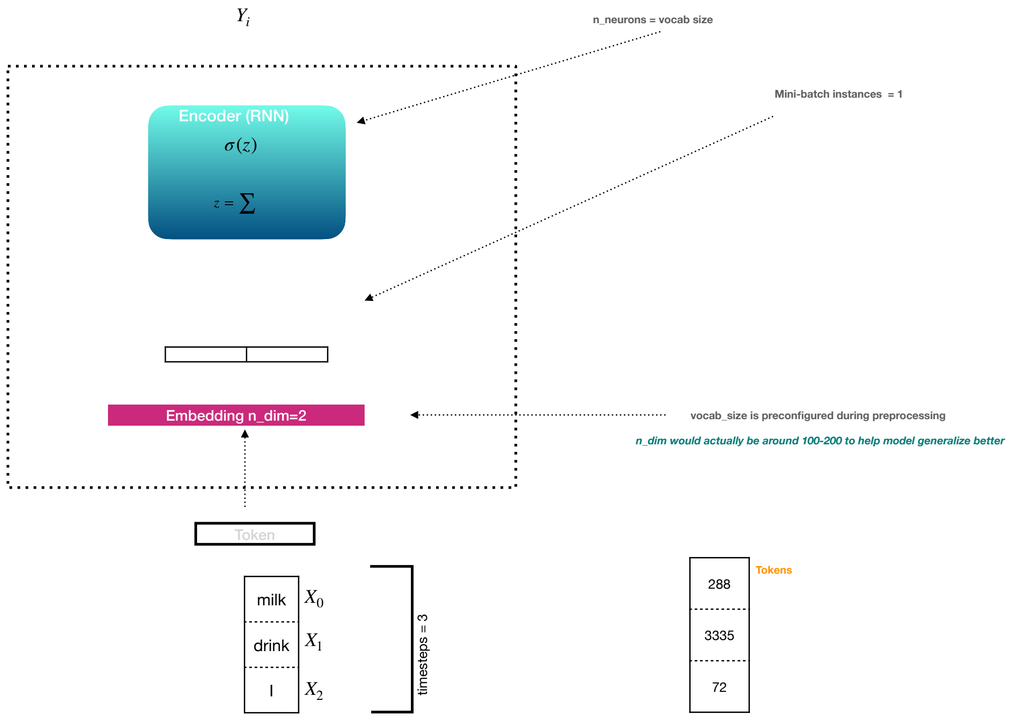
Copy model structure and weights to stateless model and enjoy inference

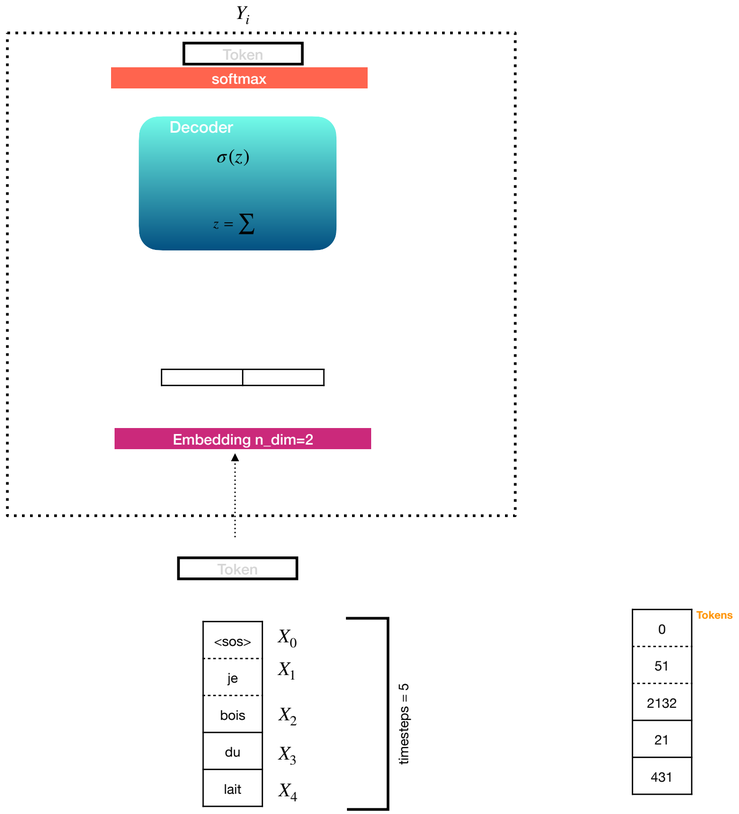
Neural Machine Translation (NMT)

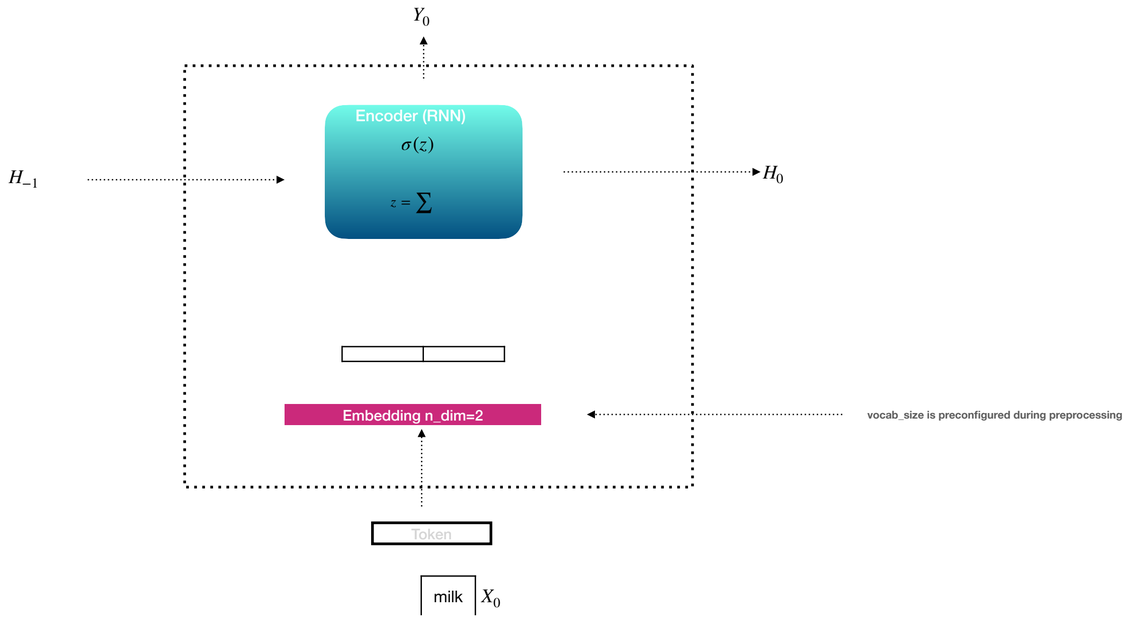


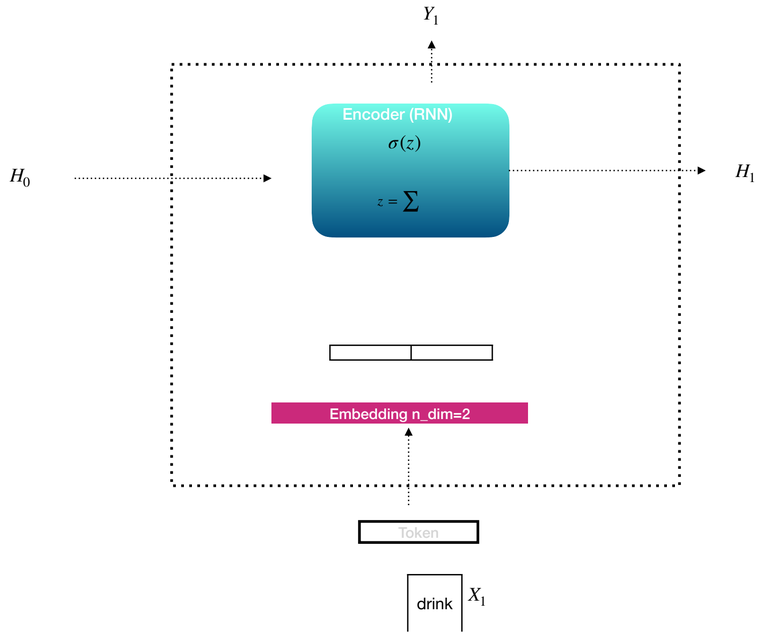
encoder learns to correlate sentence with encodings embedding

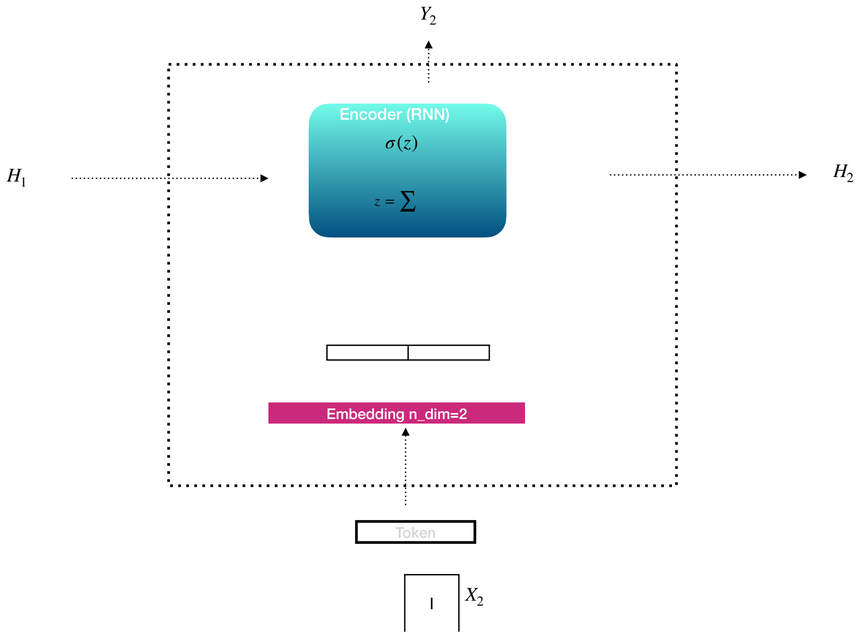



Y_i
n_neurons = vocab size
Mini-batch instances = 1
Encoder (RNN)
$\sigma(z)$
$z = \sum$
Embedding n_dim=2
vocab_size is preconfigured during preprocessing
n_dim would actually be around 100-200 to help model generalize better
Token
milk
drink
I
X_0
X_1
X_2
timesteps = 3
288
3335
72
Tokens


Y_i
Token
softmax
Decoder
$\sigma(z)$
$z = \sum$
Embedding n_dim=2
Token
<sos>
je
bois
du
lait
X_0
X_1
X_2
X_3
X_4
timesteps = 5
0
51
2132
21
431
Tokens

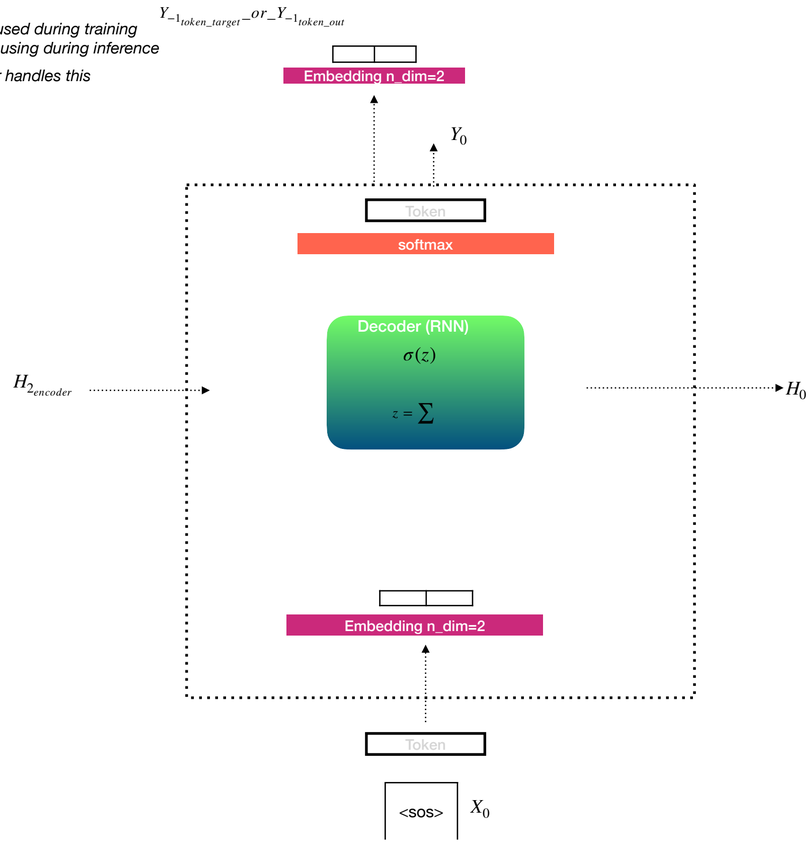

Y_0
Encoder (RNN)
$\sigma(z)$
$z = \sum$
H_{-1}
H_0
Embedding n_dim=2
vocab_size is preconfigured during preprocessing
Token
milk
X_0

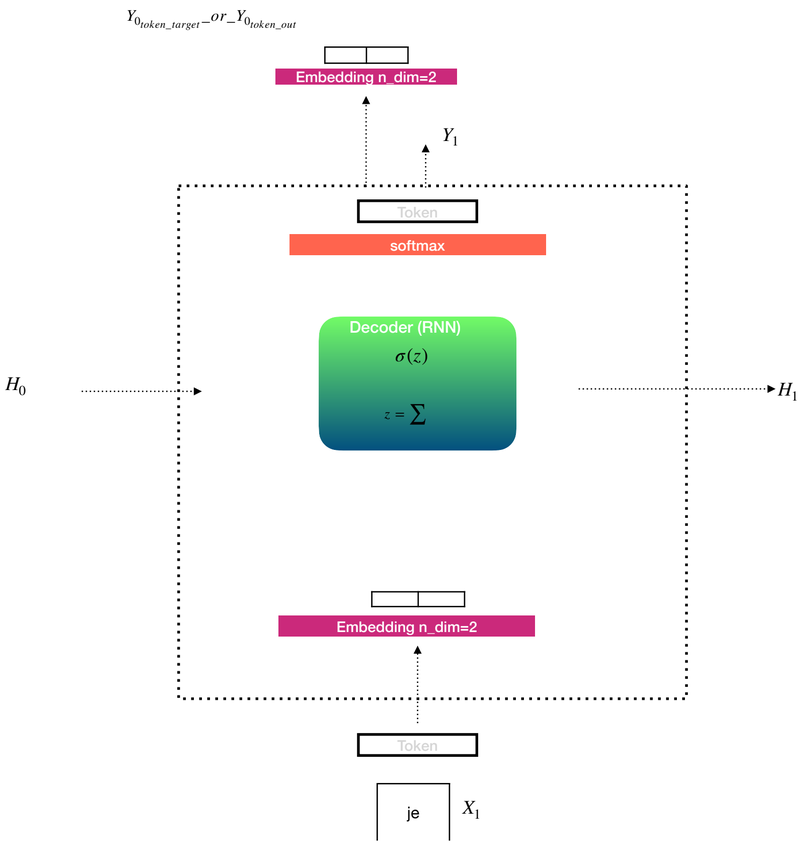

Y_1
Encoder (RNN)
$\sigma(z)$
$z = \sum$
H_0
H_1
Embedding n_dim=2
Token
drink
X_1

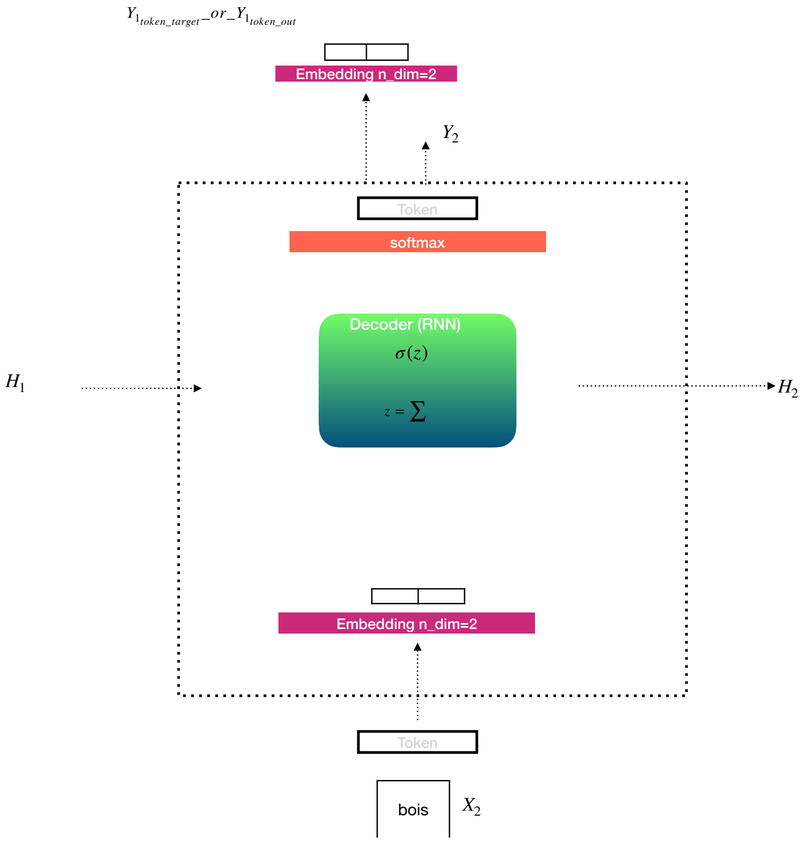

Y_2
Encoder (RNN)
$\sigma(z)$
$z = \sum$
H_1
H_2
Embedding n_dim=2
Token
I
X_2

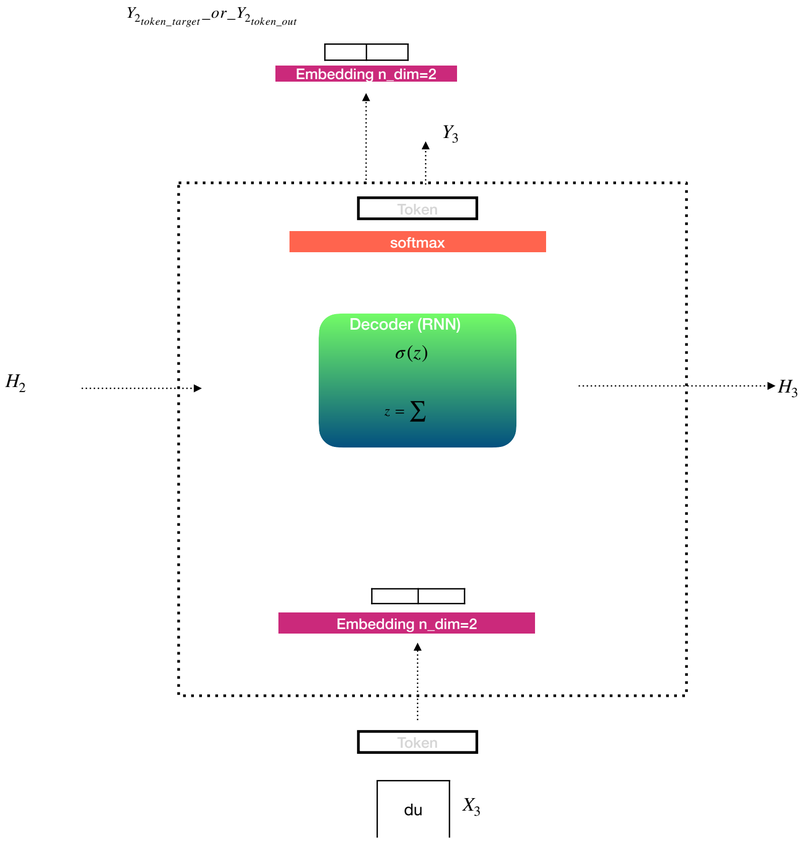
- *Prev target token used during training*
- *Prev output token using during inference*

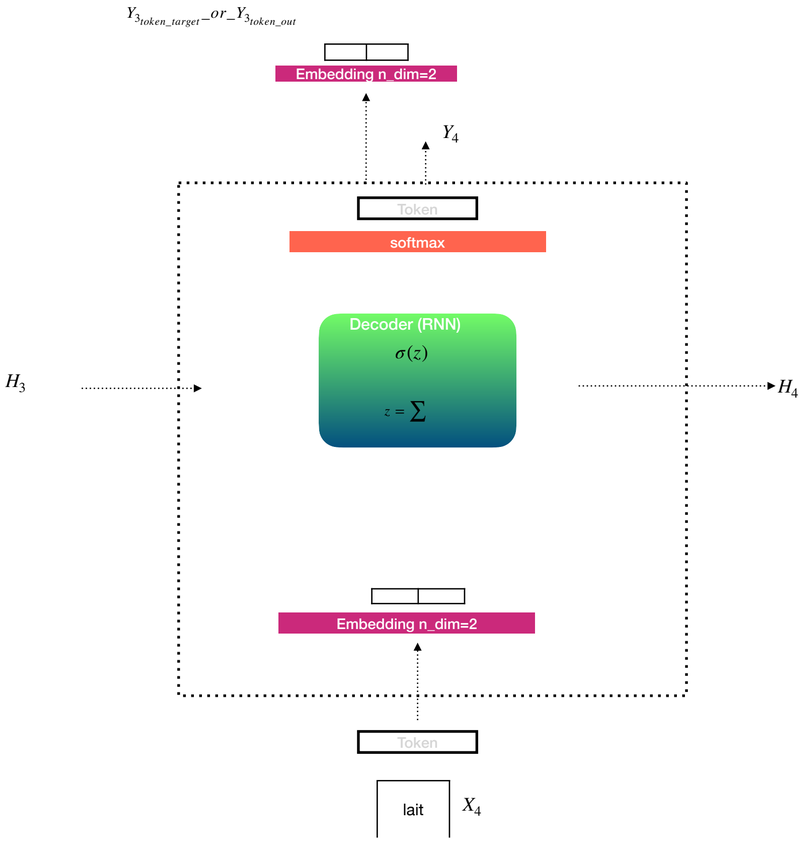
  Training sampler handles this

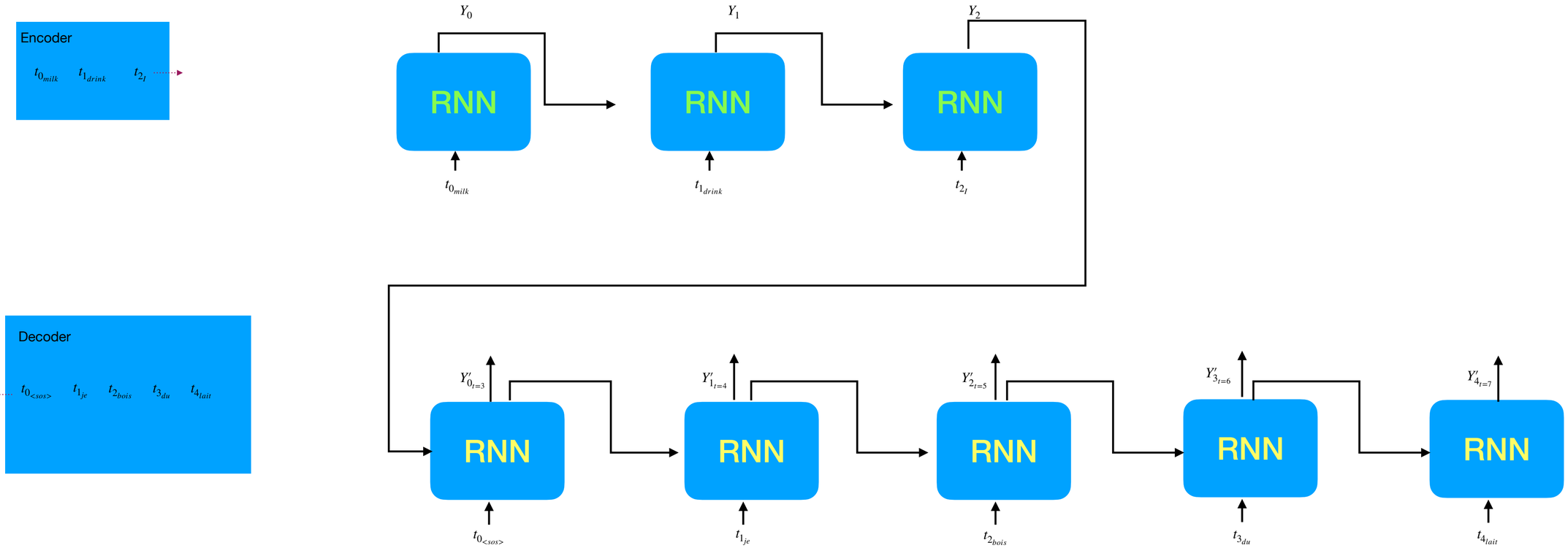



$Y_{0_{token\_target}}$ _or_ $Y_{0_{token\_out}}$
Embedding n_dim=2
Y_1
Token
softmax
Decoder (RNN)
$\sigma(z)$
$z = \sum$
H_0
H_1
Embedding n_dim=2
Token
je
X_1

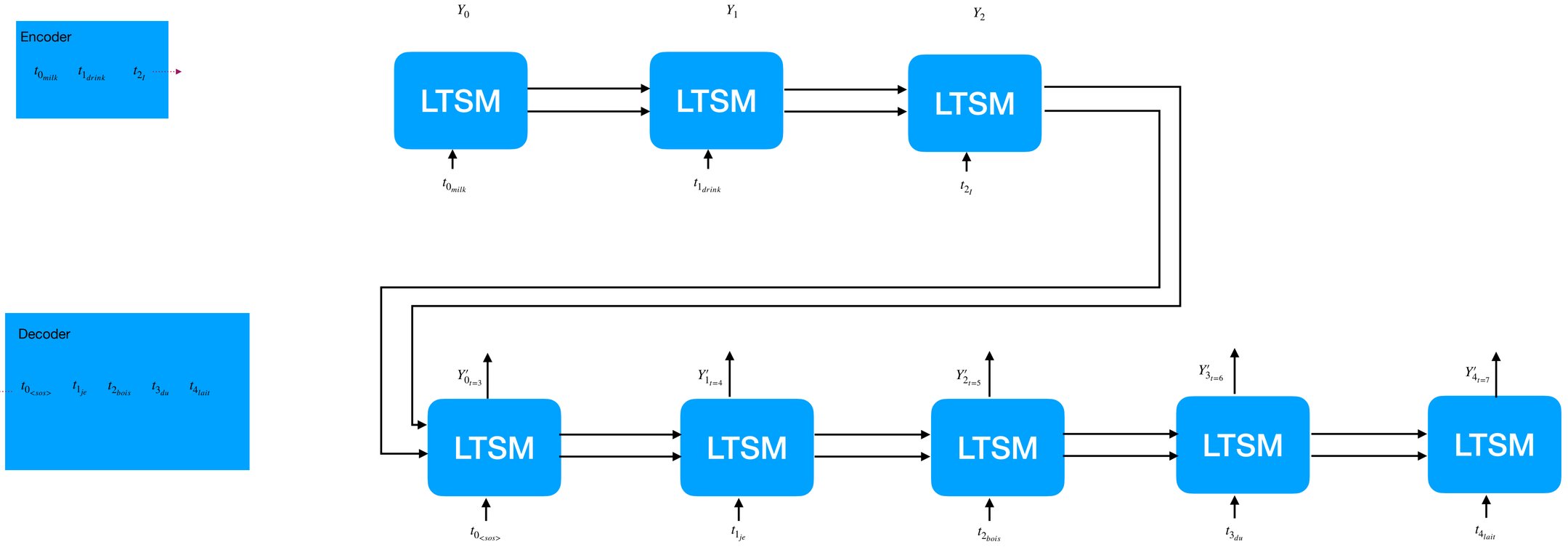

$Y_{1_{token\_target}}$ _or_ $Y_{1_{token\_out}}$
Embedding n_dim=2
Y_2
Token
softmax
Decoder (RNN)
$\sigma(z)$
$z = \sum$
H_1
H_2
Embedding n_dim=2
Token
bois
X_2


$Y_{2_{token\_target}}$ _or_ $Y_{2_{token\_out}}$
Embedding n_dim=2
Y_3
Token
softmax
Decoder (RNN)
$\sigma(z)$
$z = \sum$
H_2
H_3
Embedding n_dim=2
Token
du
X_3


$Y_{3_{token\_target}}$ _or_ $Y_{3_{token\_out}}$
Embedding n_dim=2
Y_4
Token
softmax
Decoder (RNN)
$\sigma(z)$
$z = \sum$
H_3
H_4
Embedding n_dim=2
Token
lait
X_4

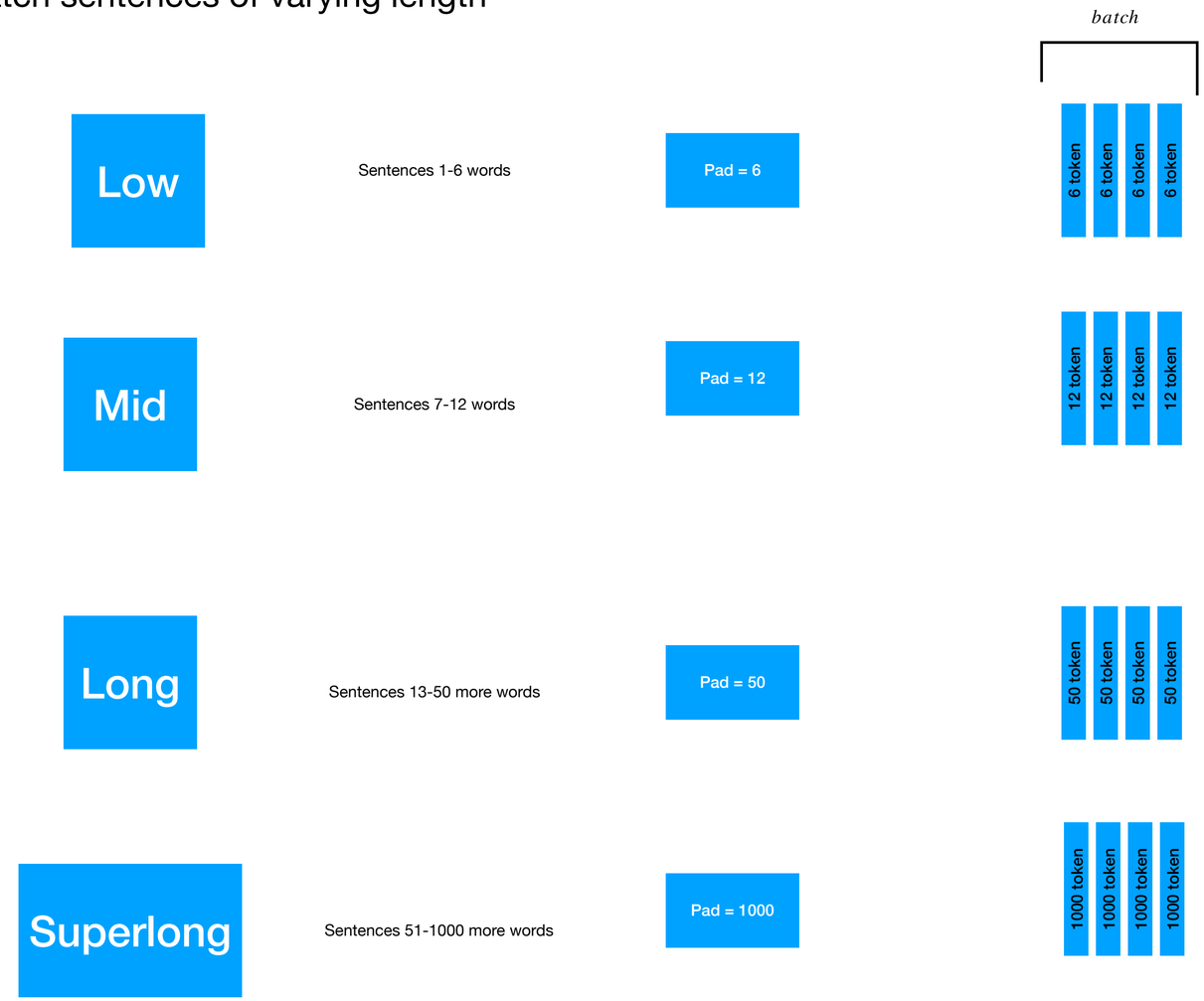


Model learns to translate English sentence into French

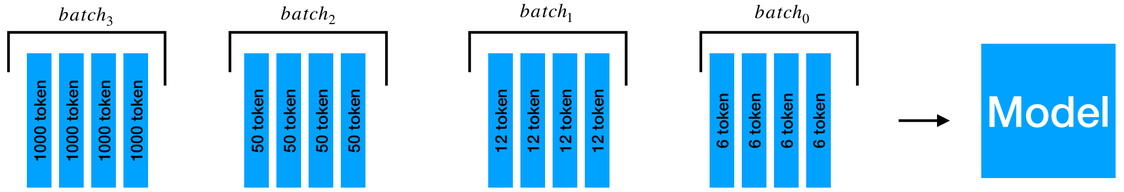


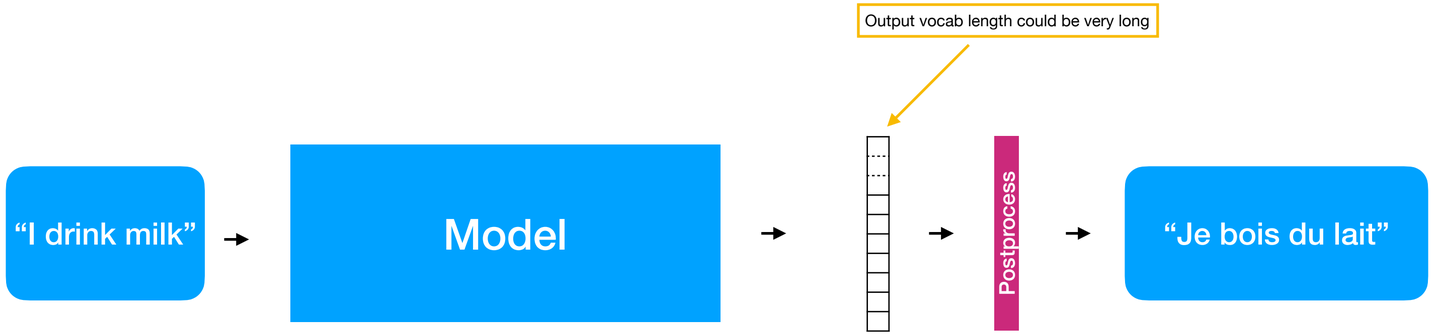
Model learns to translate English sentence into French

Batch sentences of varying length

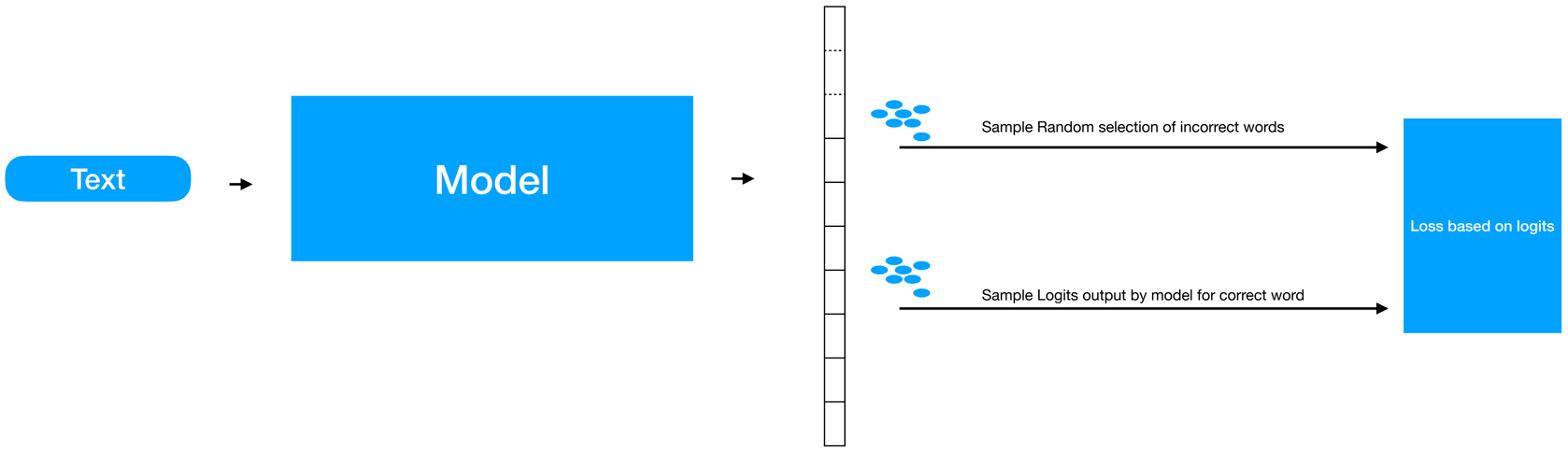


Batch of equal length Tensors are accepted as inputs to model

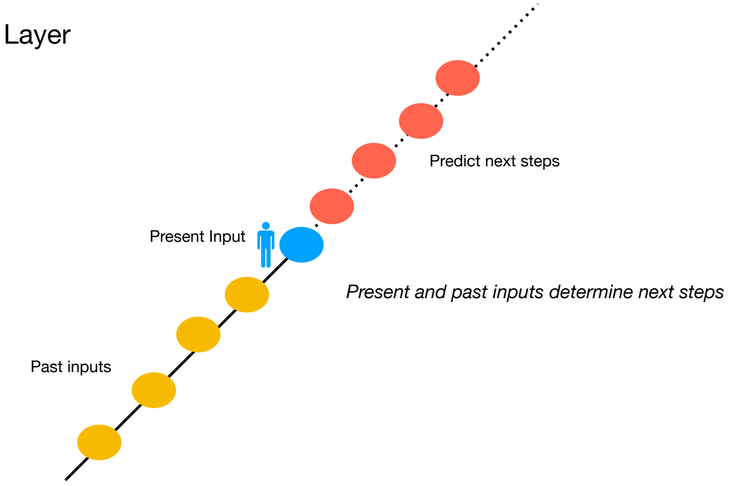



Output vocab length could be very long
“I drink milk”
Model
Postprocess
“Je bois du lait”

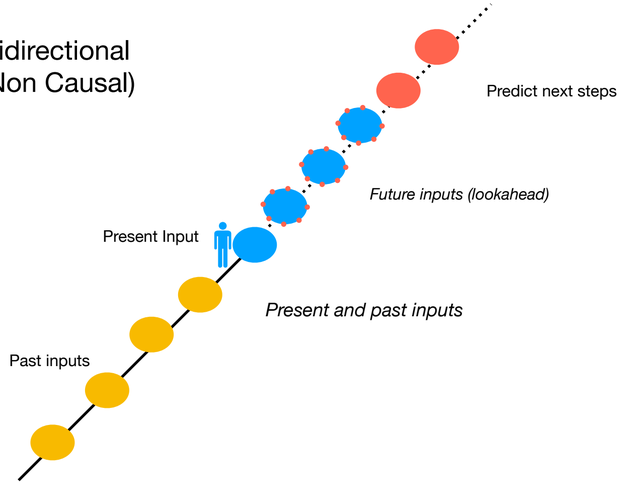
Handling large output vocab



Regular RNN Layer
(Causal)

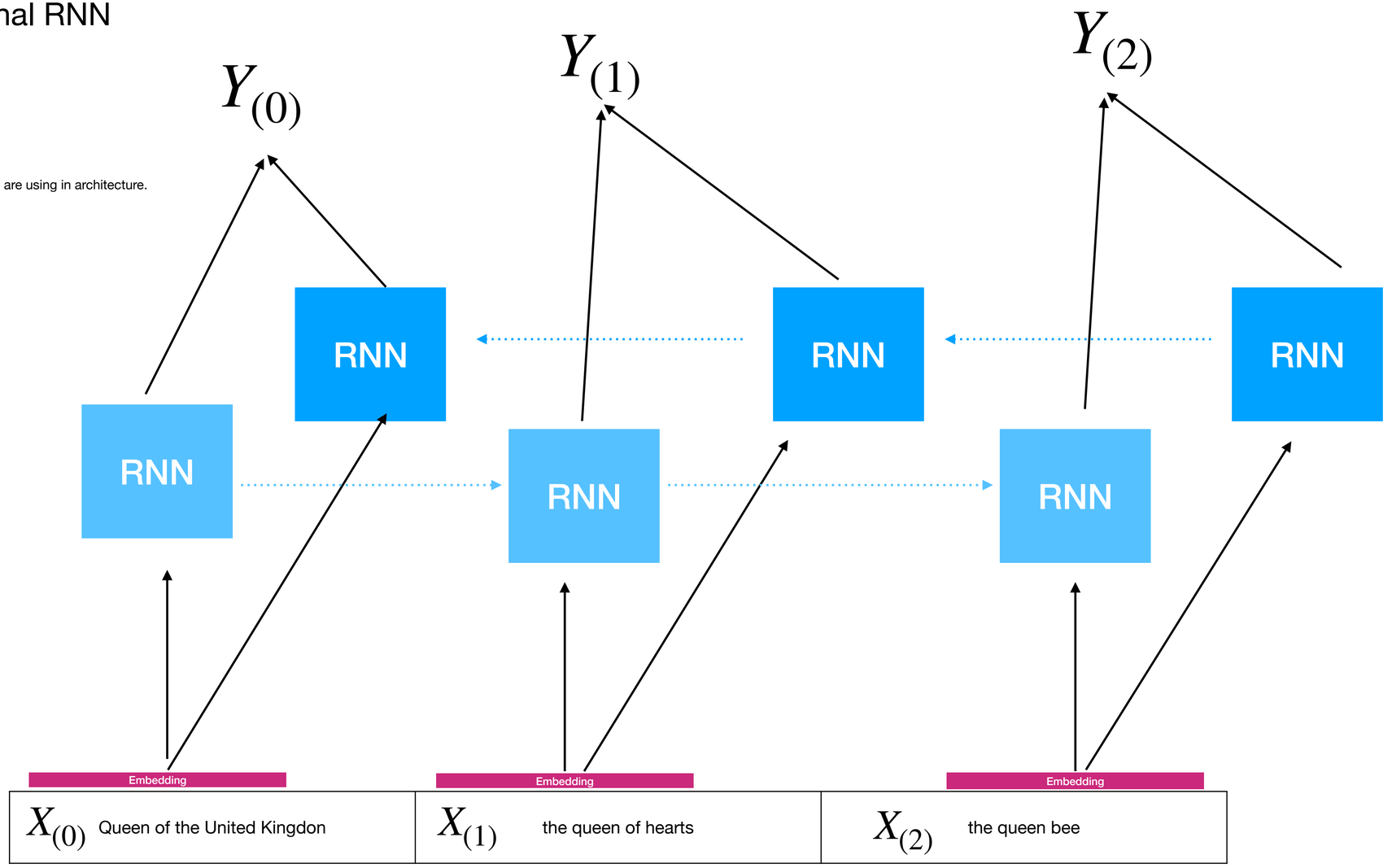


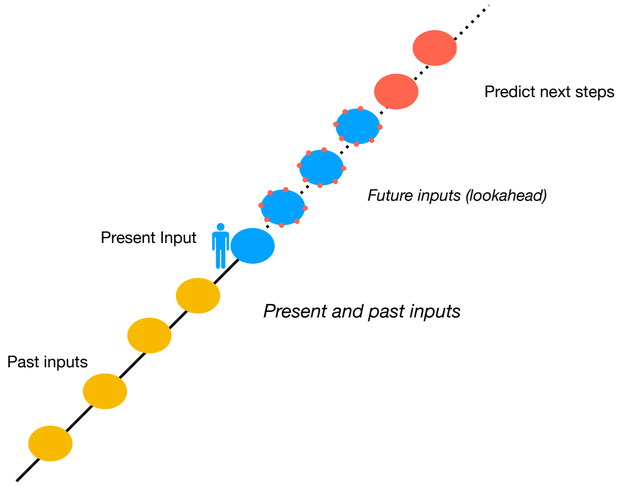
Bidirectional
(Non Causal)

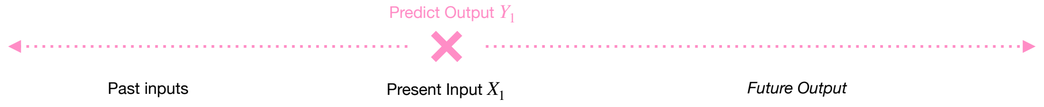


Bidirectional RNN

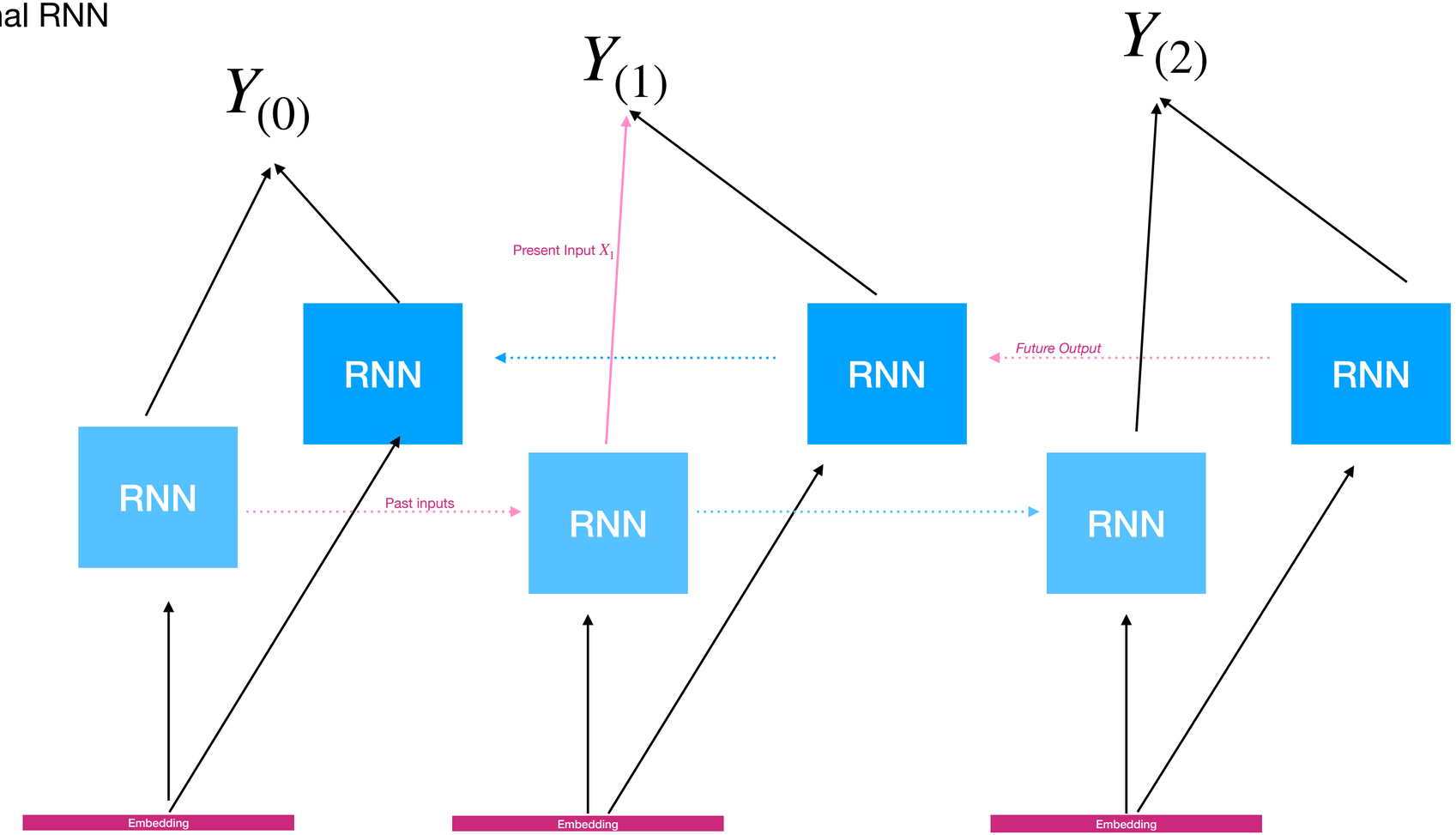
Note: Only two RNN are using in architecture.
Recursive unit!

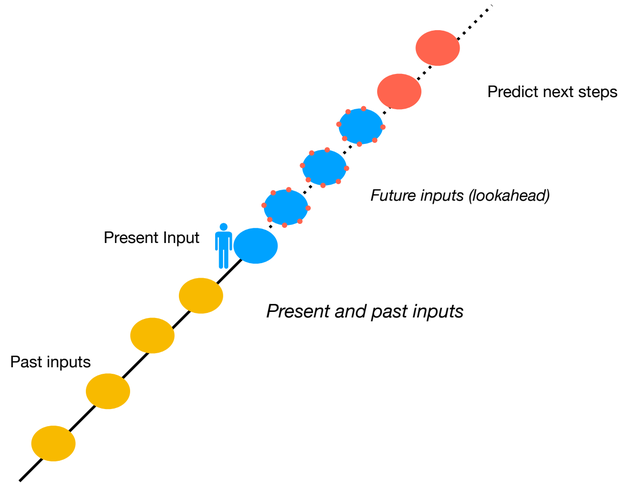






Bidirectional RNN



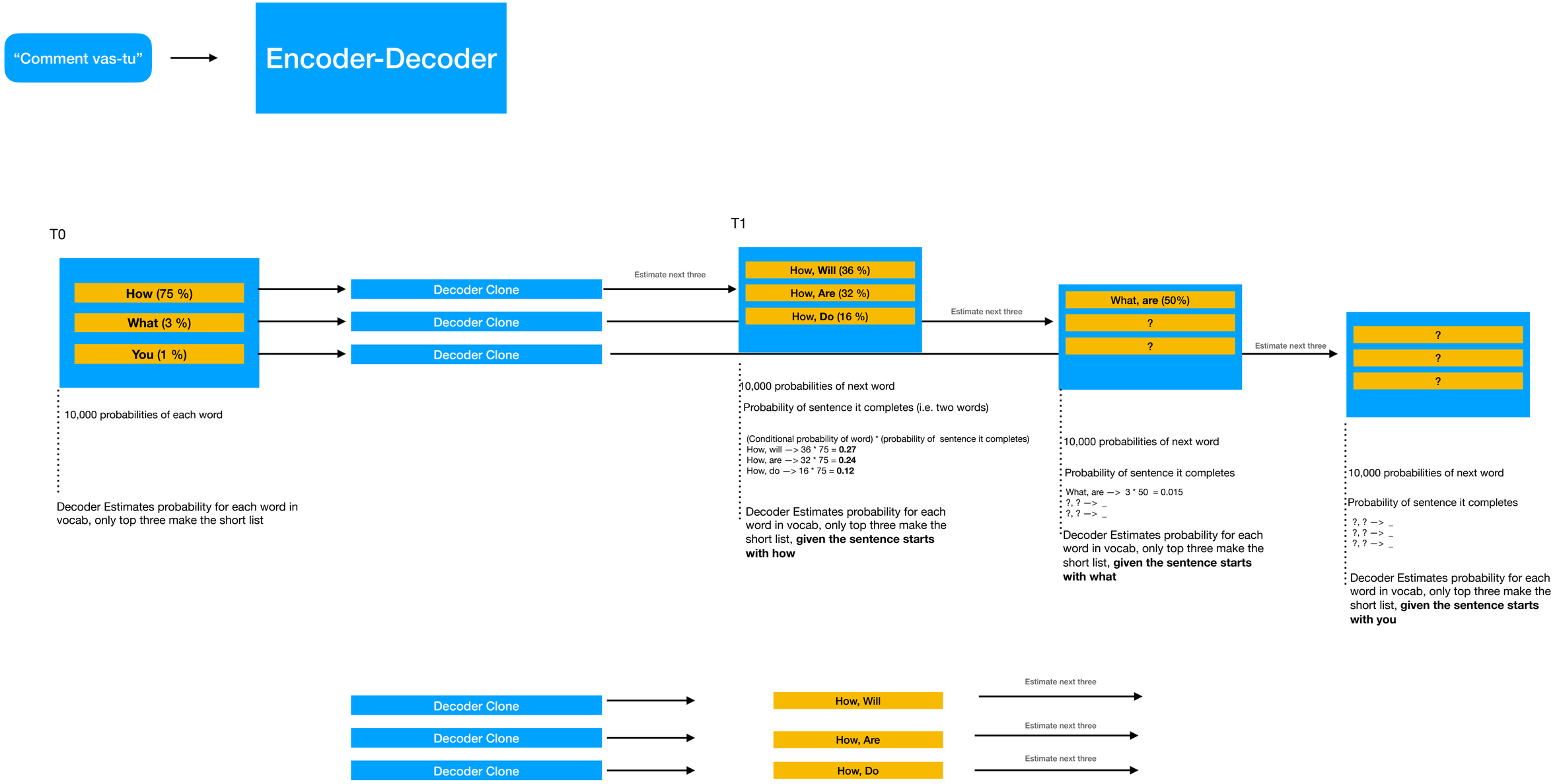


Phrases (Samples)		
Queen of the United Kingdom	the queen of hearts	the queen bee

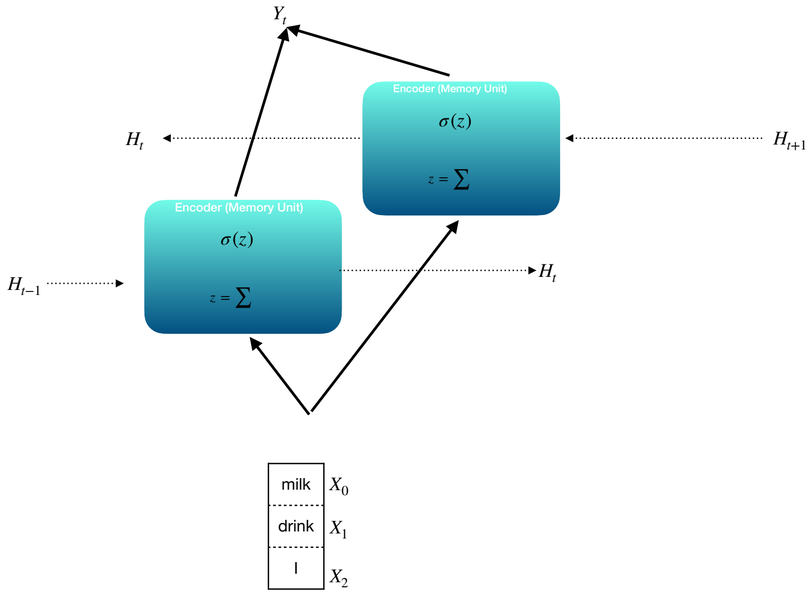
Predict Output Y_1

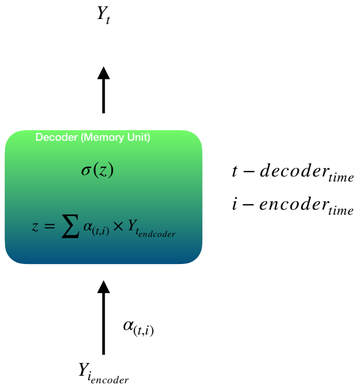
Learns next probable sentence by learning from current, present, and future phrases in different forms of English text

Beam Search (n=3)

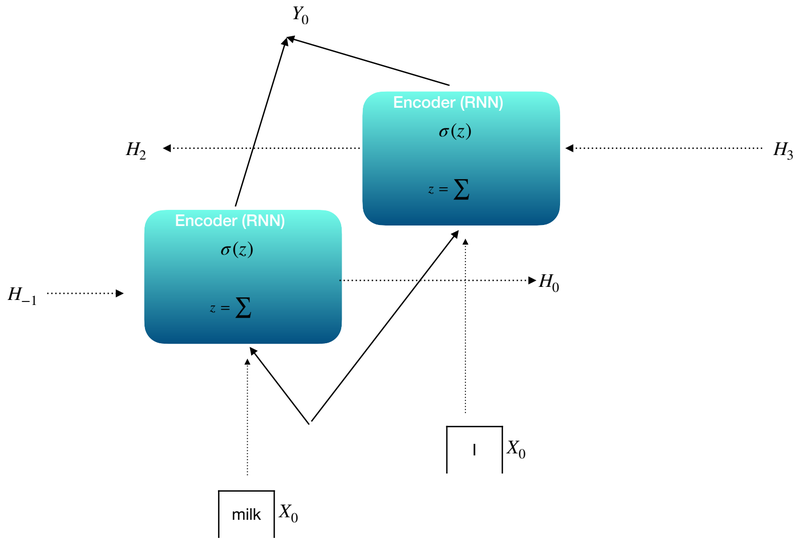


Attention Mechanisms

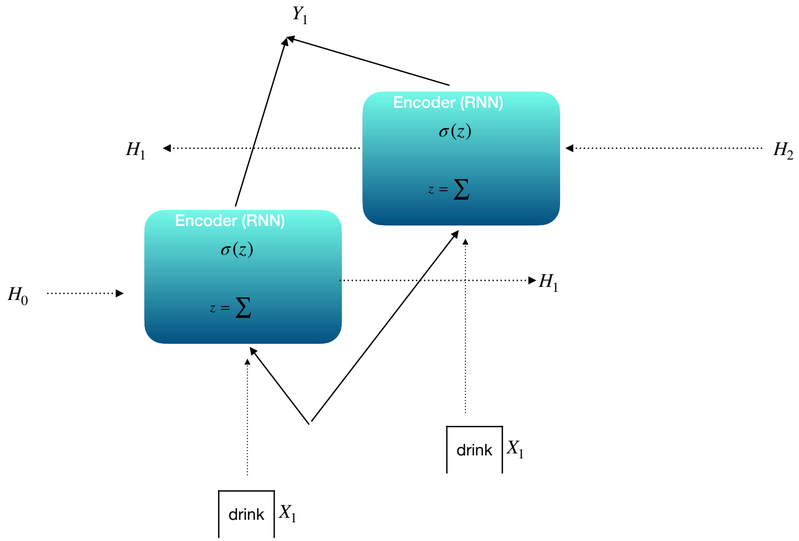




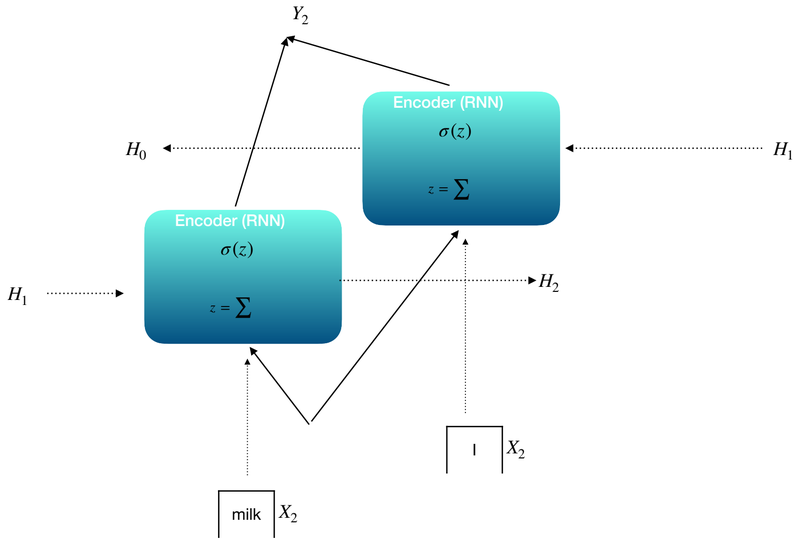
Attention Mechanisms



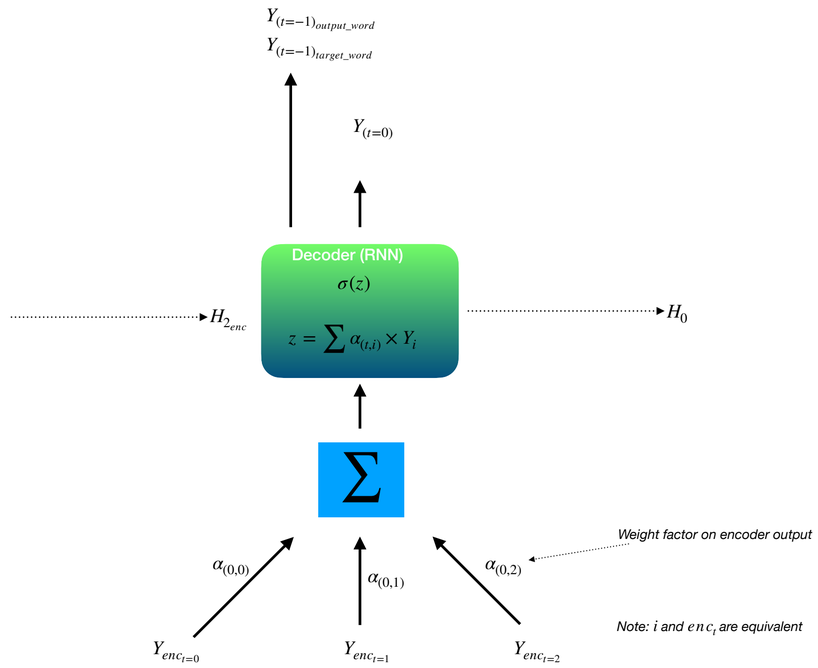
Attention Mechanisms



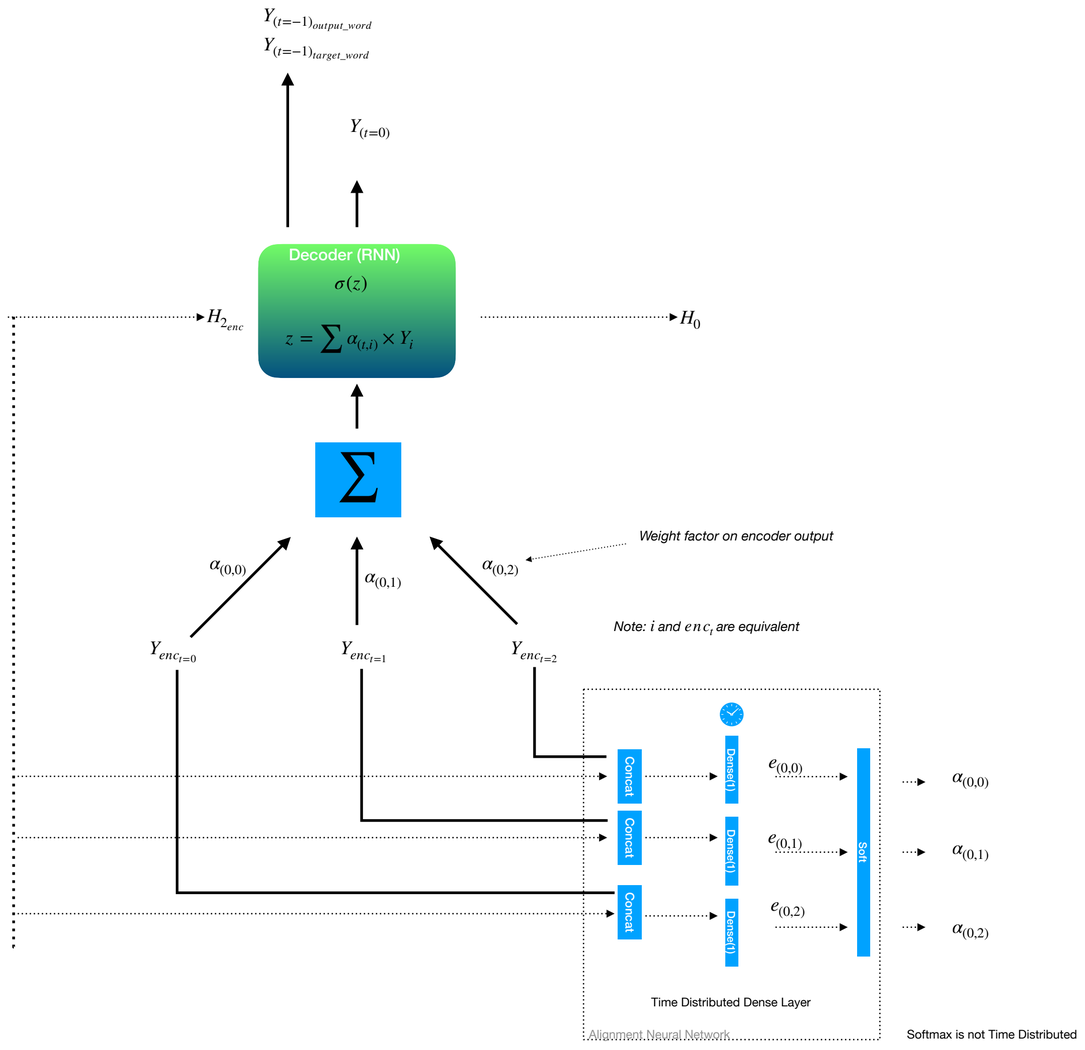
Attention Mechanisms



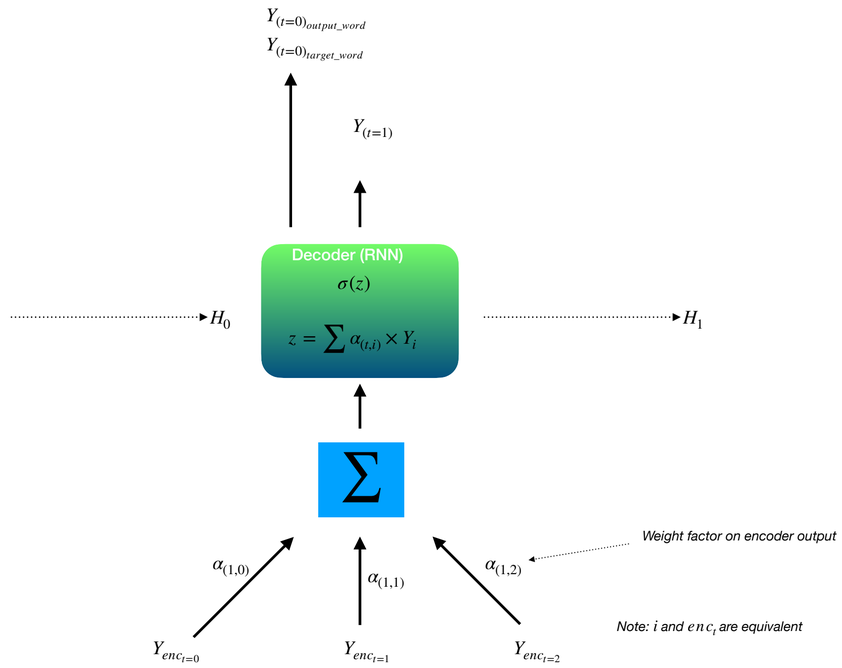
Attention Mechanisms



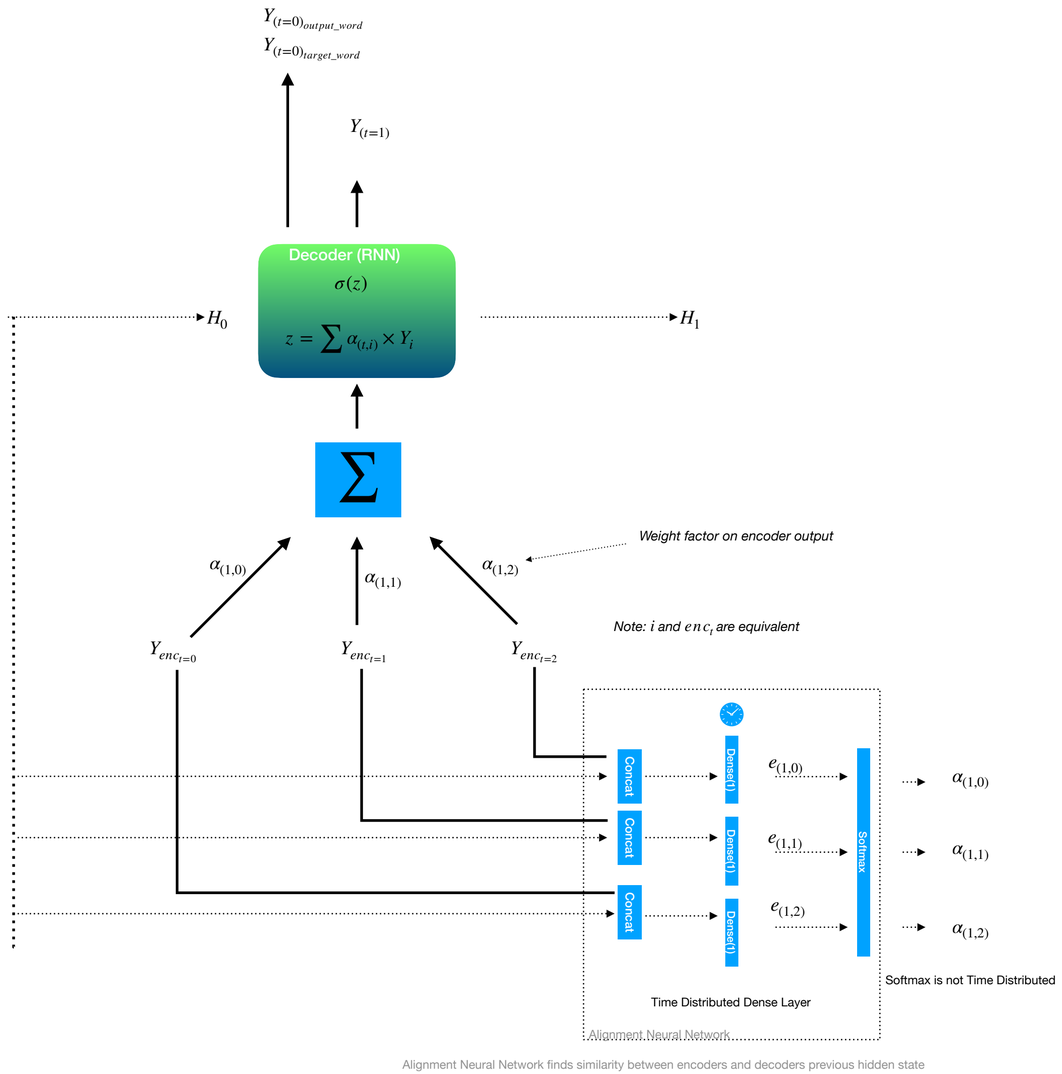
Attention Mechanisms:
Calculating Weights



Attention Mechanisms

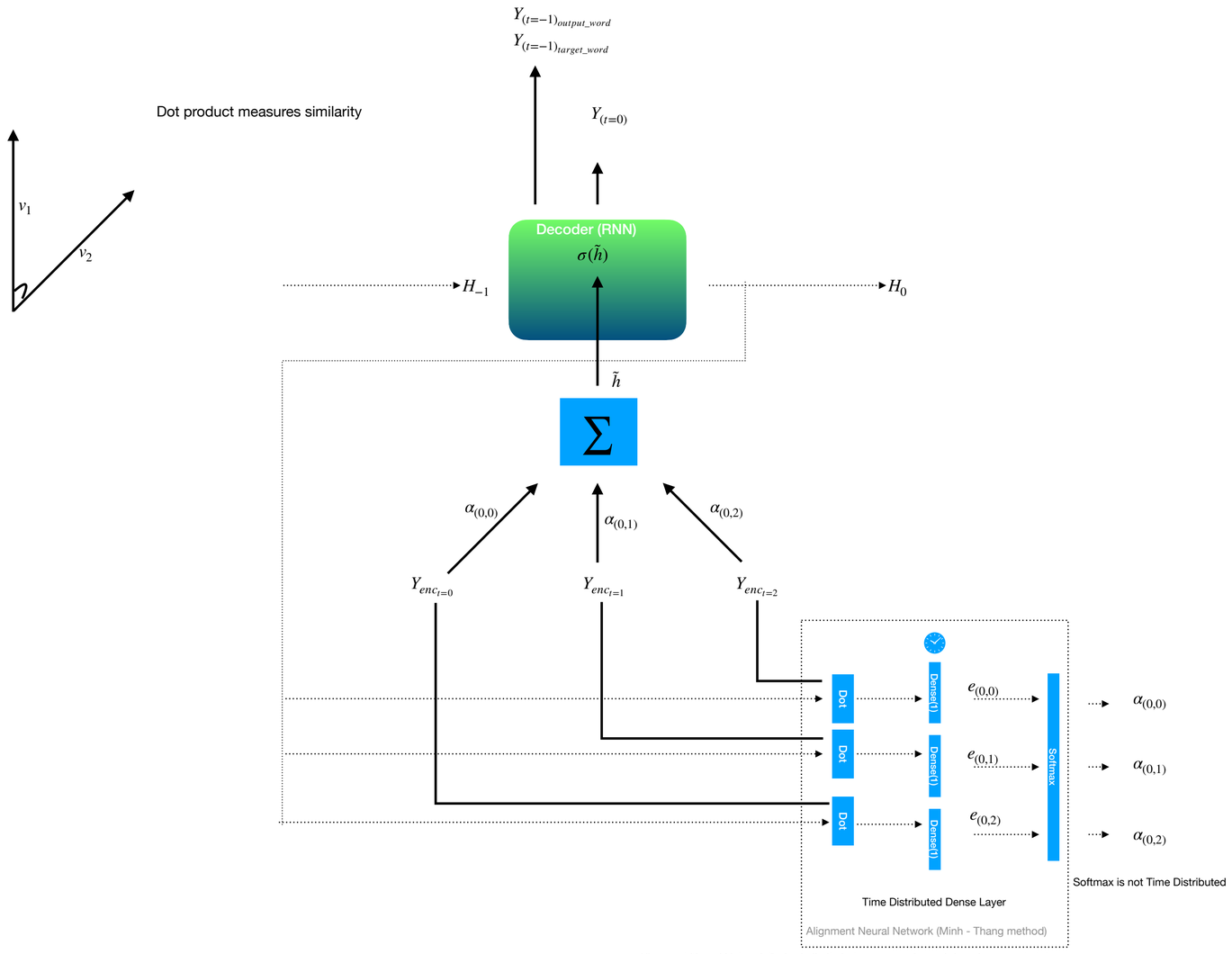


Attention Mechanisms:
Calculating Weights

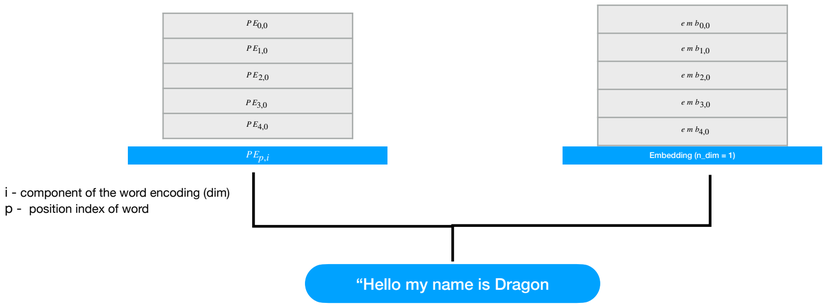


Alignment Neural Network finds similarity between encoders and decoders previous hidden state

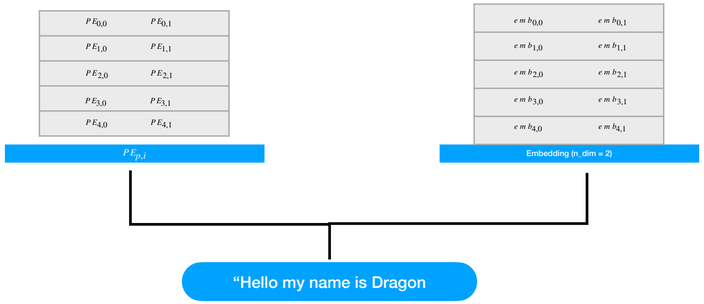
Attention Mechanisms
(Method 2)



Positional Encodings

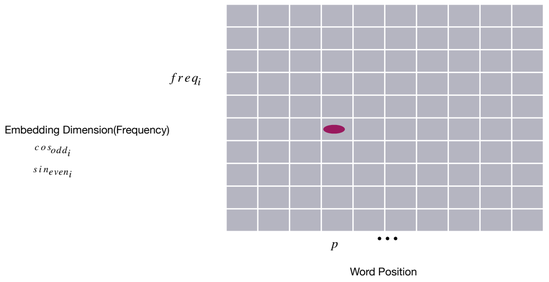


$$PE_{p,i} = \begin{cases} sin(p/10000^{i/d}) & \text{if i is even} \\ cos(p/10000^{(i-1)/d}) & \text{if i is odd} \end{cases}$$

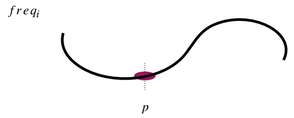


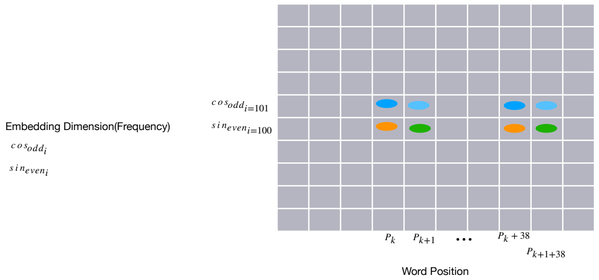
Positional Encodings

$$PE_{p,i} = \begin{cases} sin(p/10000^{i/d}) & \text{if i is even} \\ cos(p/10000^{(i-1)/d}) & \text{if i is odd} \end{cases}$$

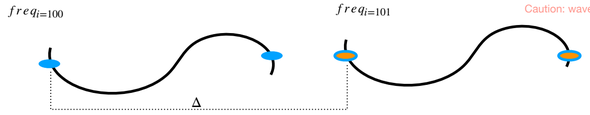


Note: Unique positional encoding at different frequencies (i) and positions(p)



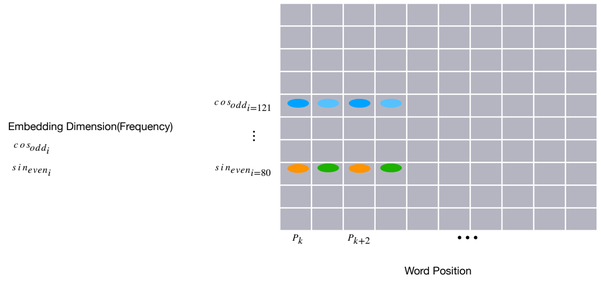


Words located 38 word distances apart have a positional encoding in dimensions 100 and 101



Caution: wave are not representative of cos and sin waves; strictly placeholders

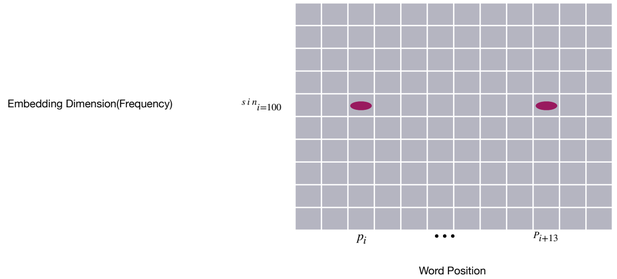
Both sin and cos required for PE encoding to generate unique relative word positions.

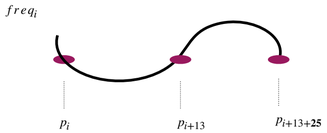


Words located 2 word distances apart have a positional encoding in dimensions 80 and 121

Positional Encodings

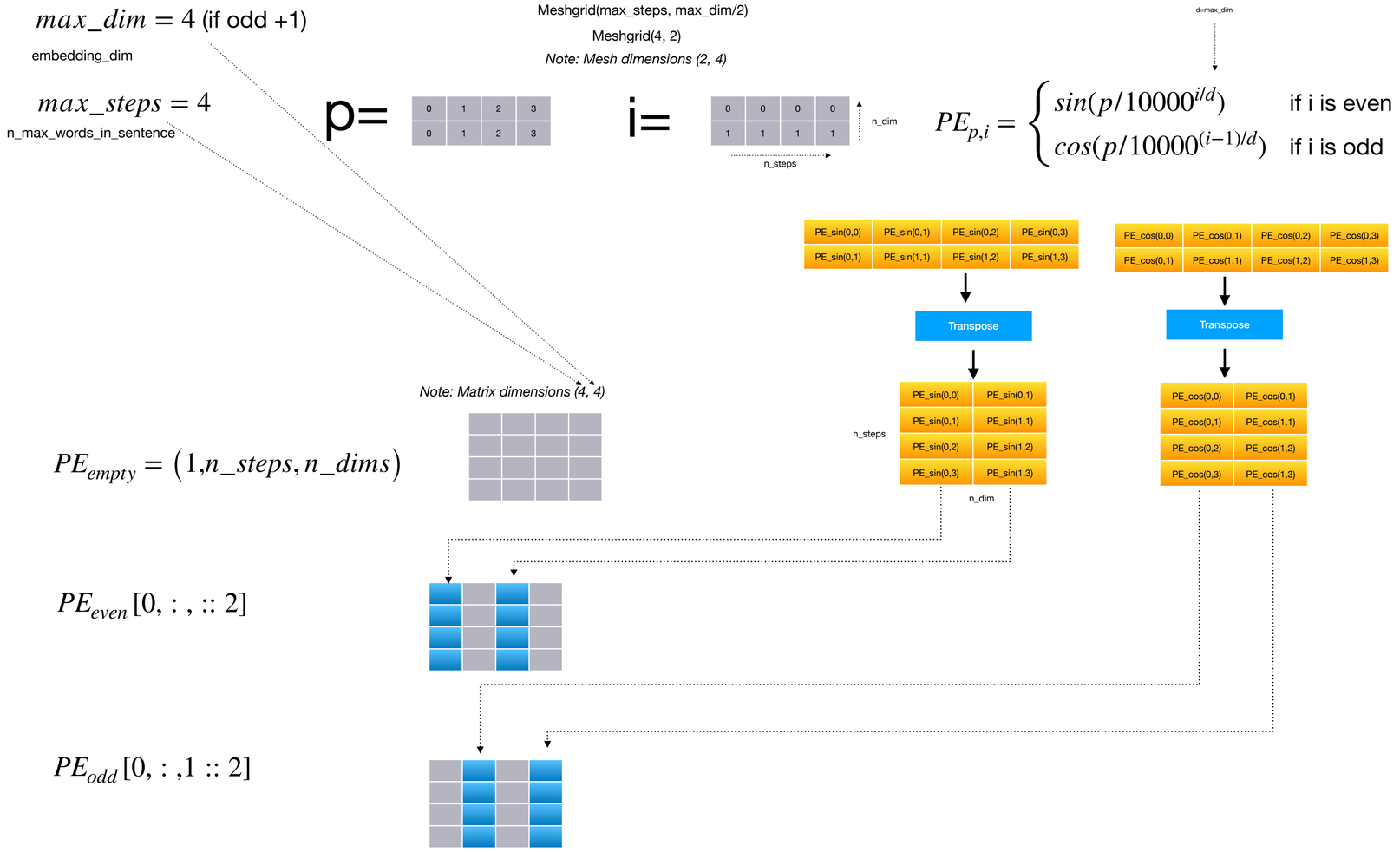
$$PE_{p,i} = \begin{cases} sin(p/10000^{i/d}) \\ \cancel{cos(p/10000^{(i-1)/d})} \end{cases} \quad \text{for all}$$



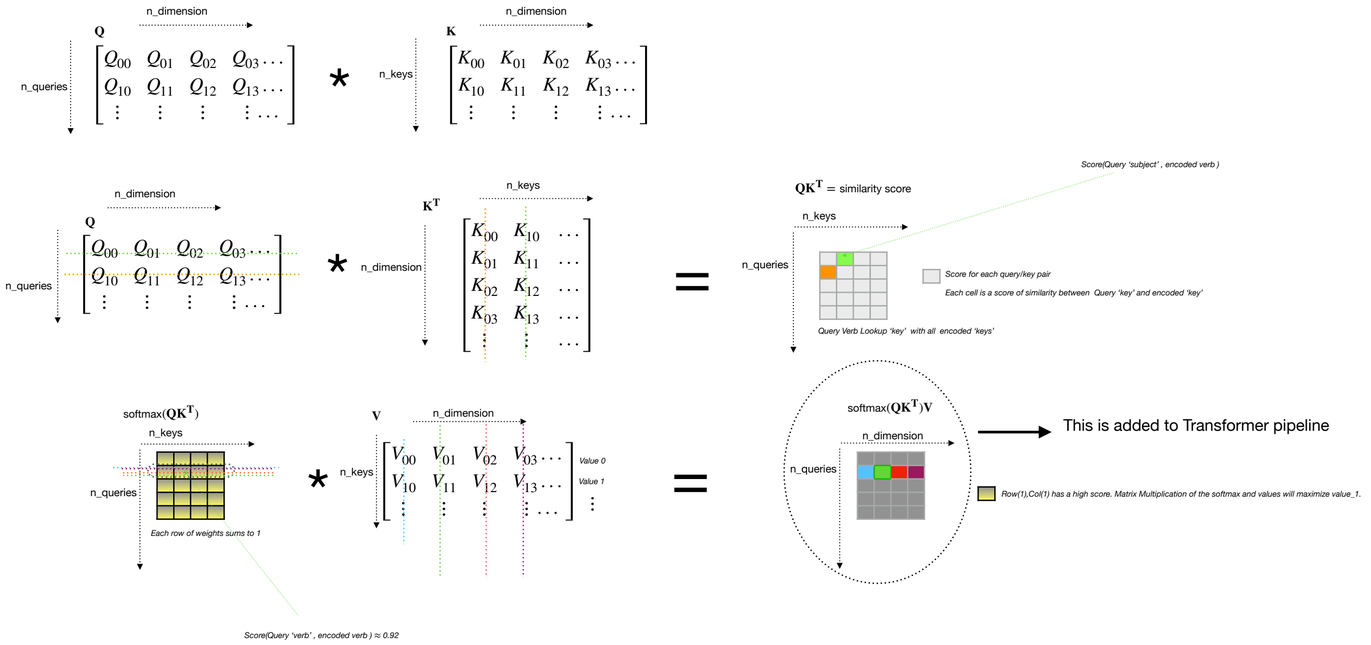


Deltas are not unique. This is an example of aliasing. Model cannot learn from ambiguous encoding.

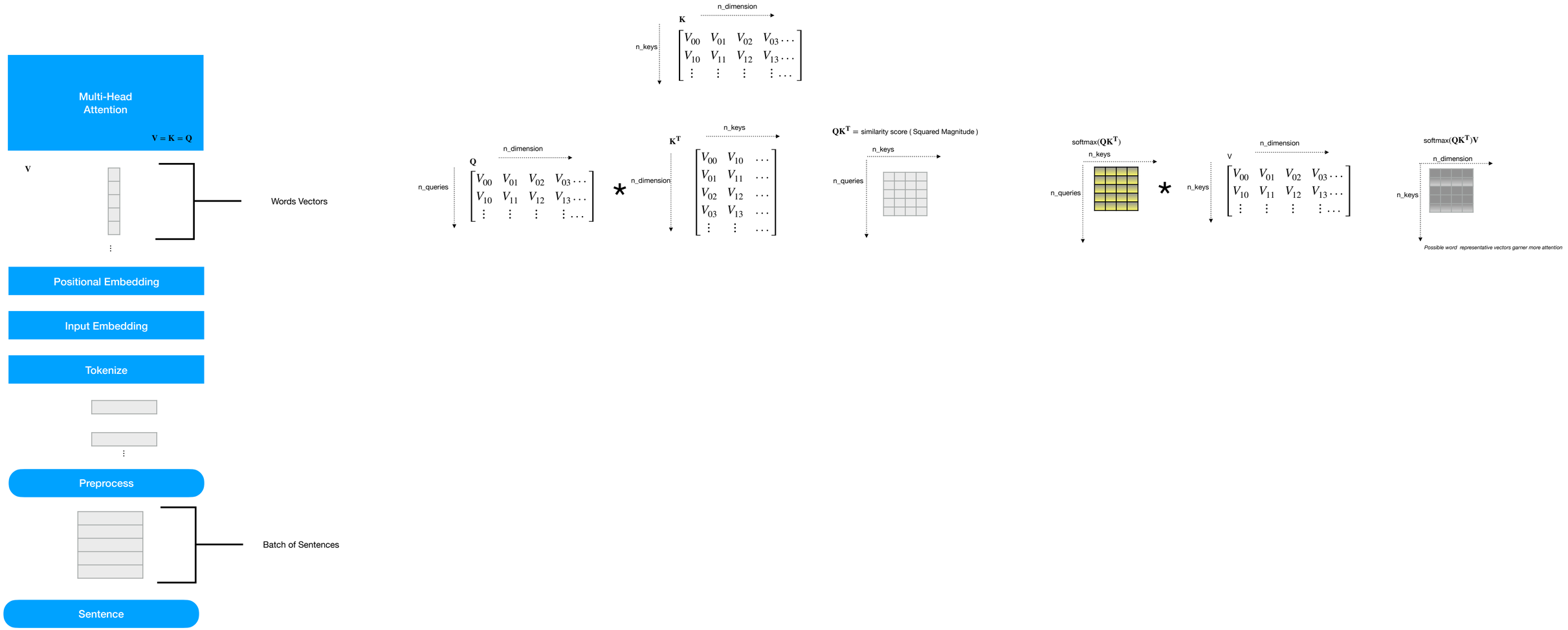
Positional Encodings : Simple Example



MultiHead Attention Layer

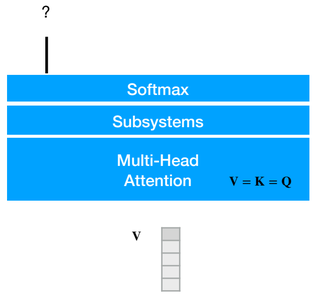


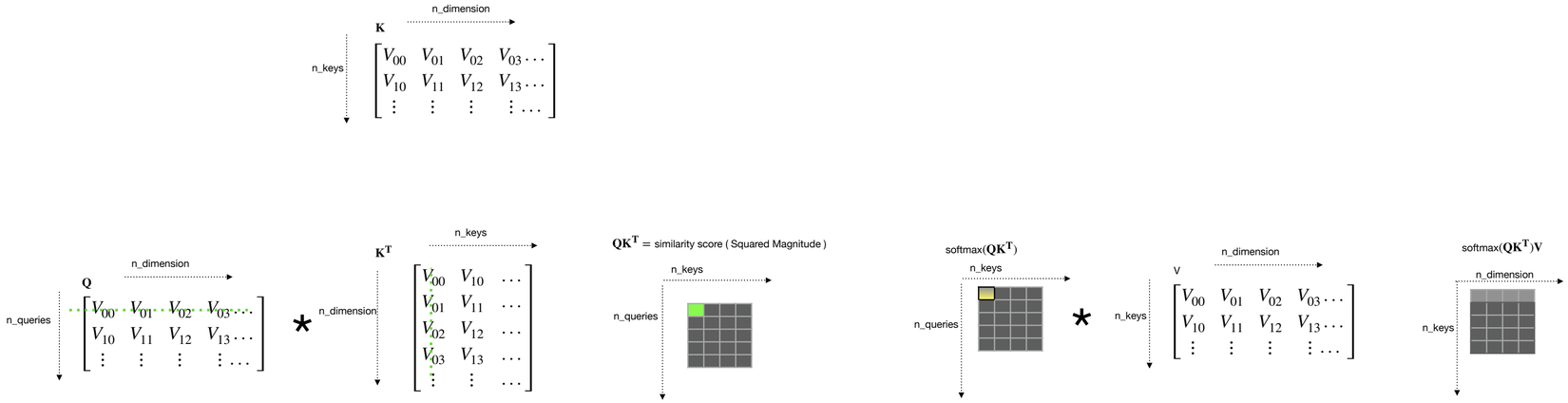
MultiHead Attention Layer : Encoder Subsystem

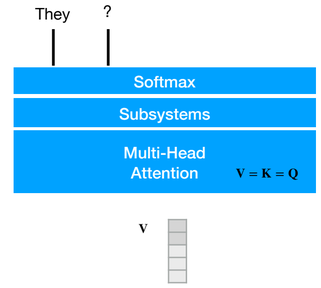


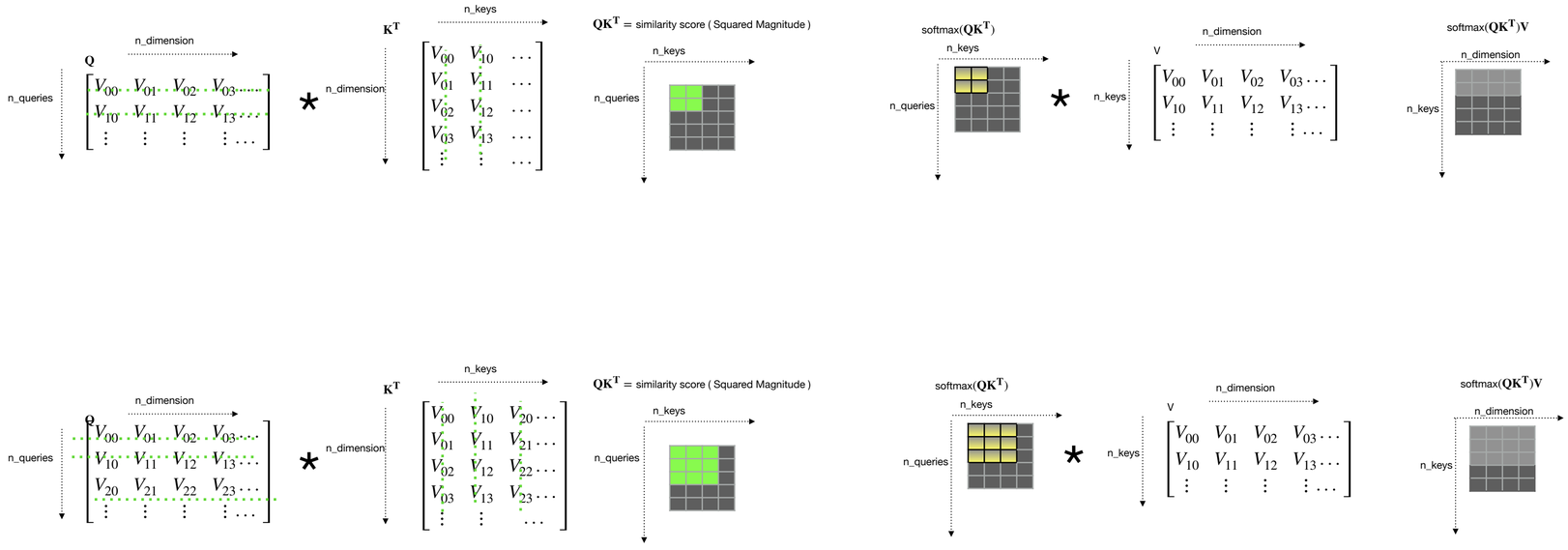
MaskedMultiHead Attention Layer : Decoder Subsystem

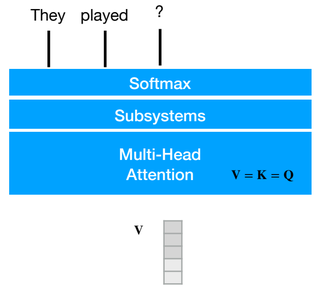
Mask MH Attention. Words cannot compare to words in the future.
Prevent a word from comparing itself to words located after it.
Masking can be done by adding large negative number to
$\mathbf{QK^T}$ = similarity score (Squared Magnitude)



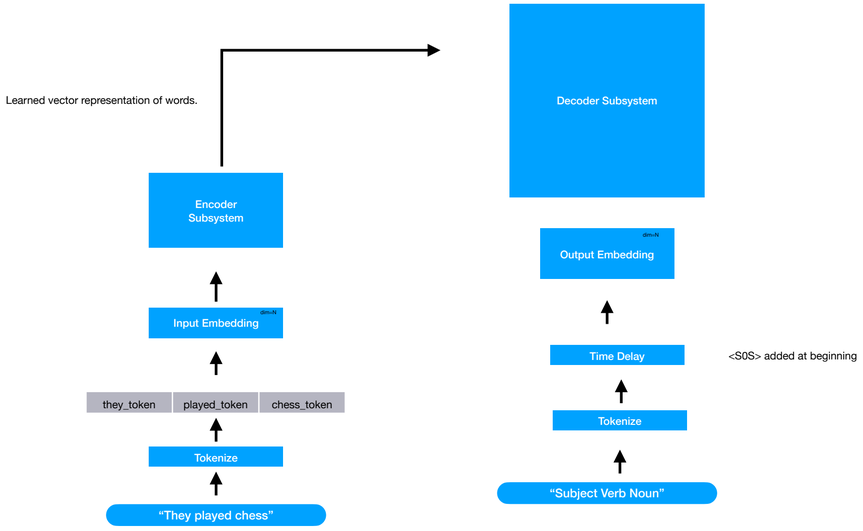


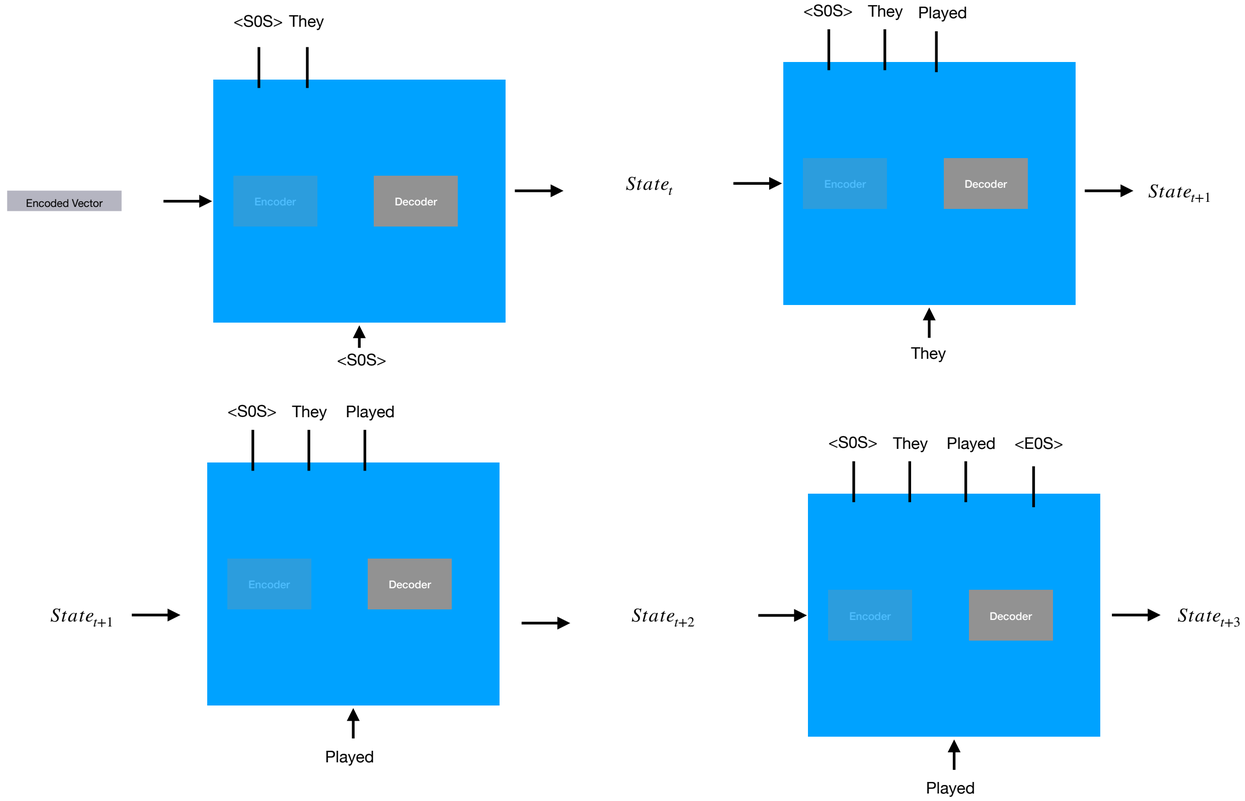




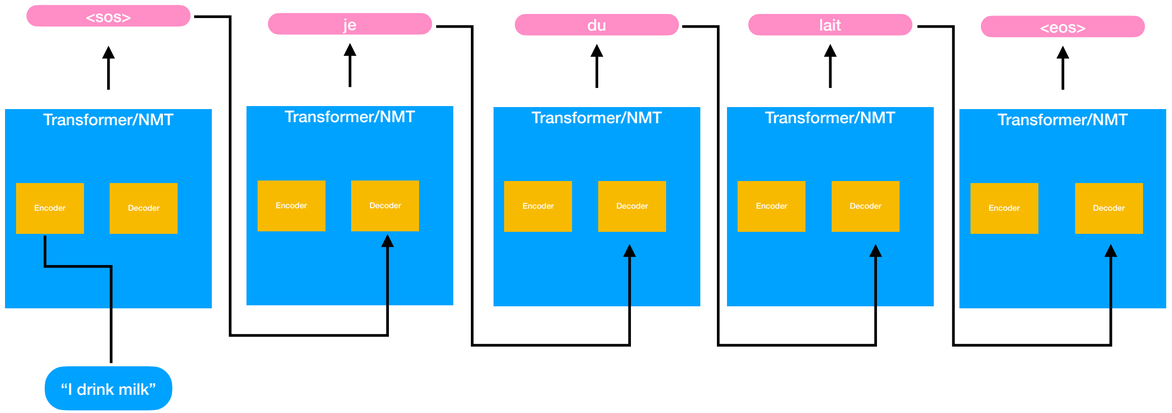


Train/ Infer


Learned vector representation of words.
Encoder Subsystem
Input Embedding
dim=N
they_token
played_token
chess_token
Tokenize
“They played chess”
Decoder Subsystem
Output Embedding
dim=N
Time Delay
Tokenize
“Subject Verb Noun”
<S0S> added at beginning


<S0S> They
Encoded Vector
Encoder
Decoder
<S0S>
$State_t$
<S0S> They Played
Encoder
Decoder
They
$State_{t+1}$
$State_{t+1}$
<S0S> They Played
Encoder
Decoder
Played
$State_{t+2}$
<S0S> They Played <E0S>
Encoder
Decoder
Played
$State_{t+3}$

Inference


<sos>
je
du
lait
<eos>
Transformer/NMT
Encoder
Decoder
"I drink milk"