Introduction to machine translation

MACHINE TRANSLATION IN PYTHON

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Machine translation

Привет

හෙලෝ

Hola

Hallo

Bonjour

你好

Olá

Machine translation

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Hello

Course outline

- Chapter 1 - Introduction to machine translation
- Chapter 2 - Implement a machine translation model (encoder-decoder architecture)
- Chapter 3 - Training the model and generating translations
- Chapter 4 - Improving the translation model

Dataset (English-French sentence corpus)

- English corpus

```
new jersey is sometimes quiet during autumn , and it is snowy in april .
the united states is usually chilly during july , and it is usually freezing ...
california is usually quiet during march , and it is usually hot in june .
```

- French corpus

```
new jersey est parfois calme pendant l' automne , et il est neigeux en avril .
les états-unis est généralement froid en juillet , et il gèle habituellement ...
california est généralement calme en mars , et il est généralement chaud en juin .
```

[1] https://github.com/udacity/deep [2] learning/tree/master/language [3] translation/data

Machine translation - Overview

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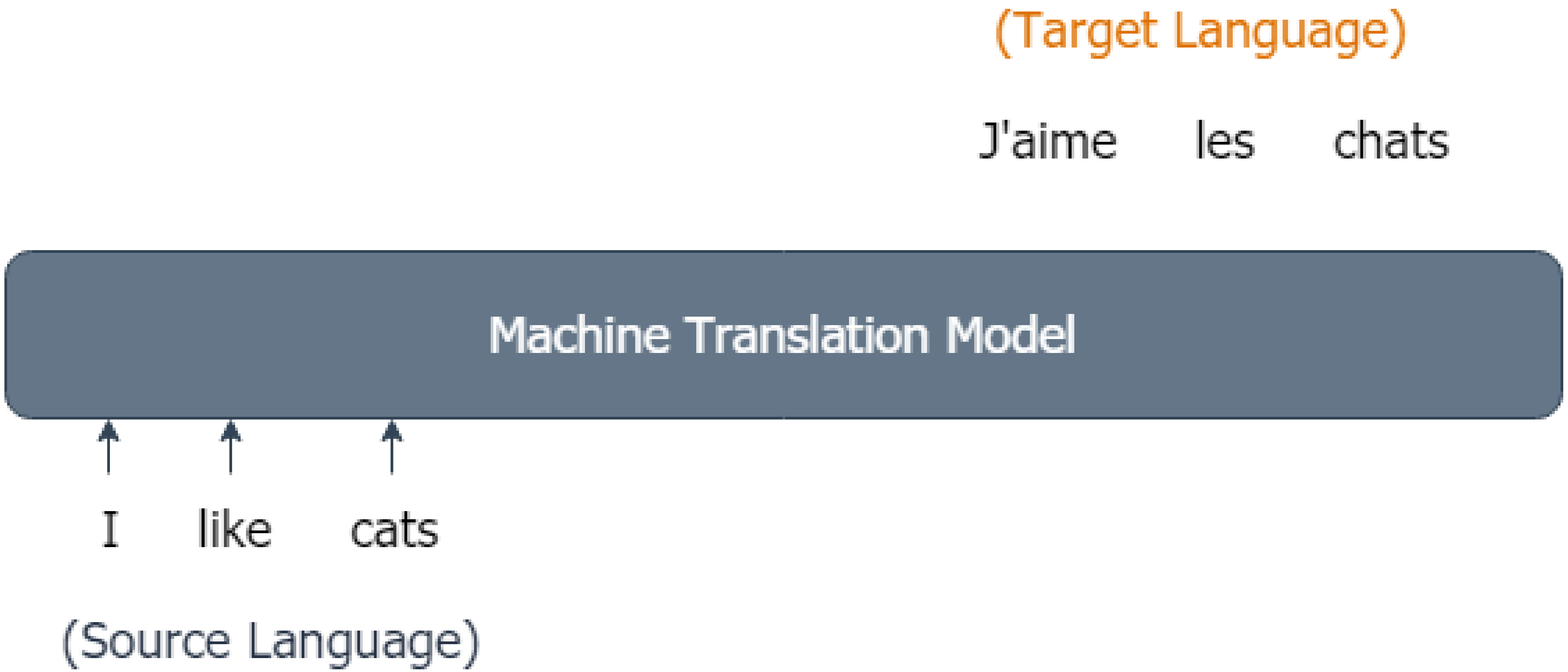
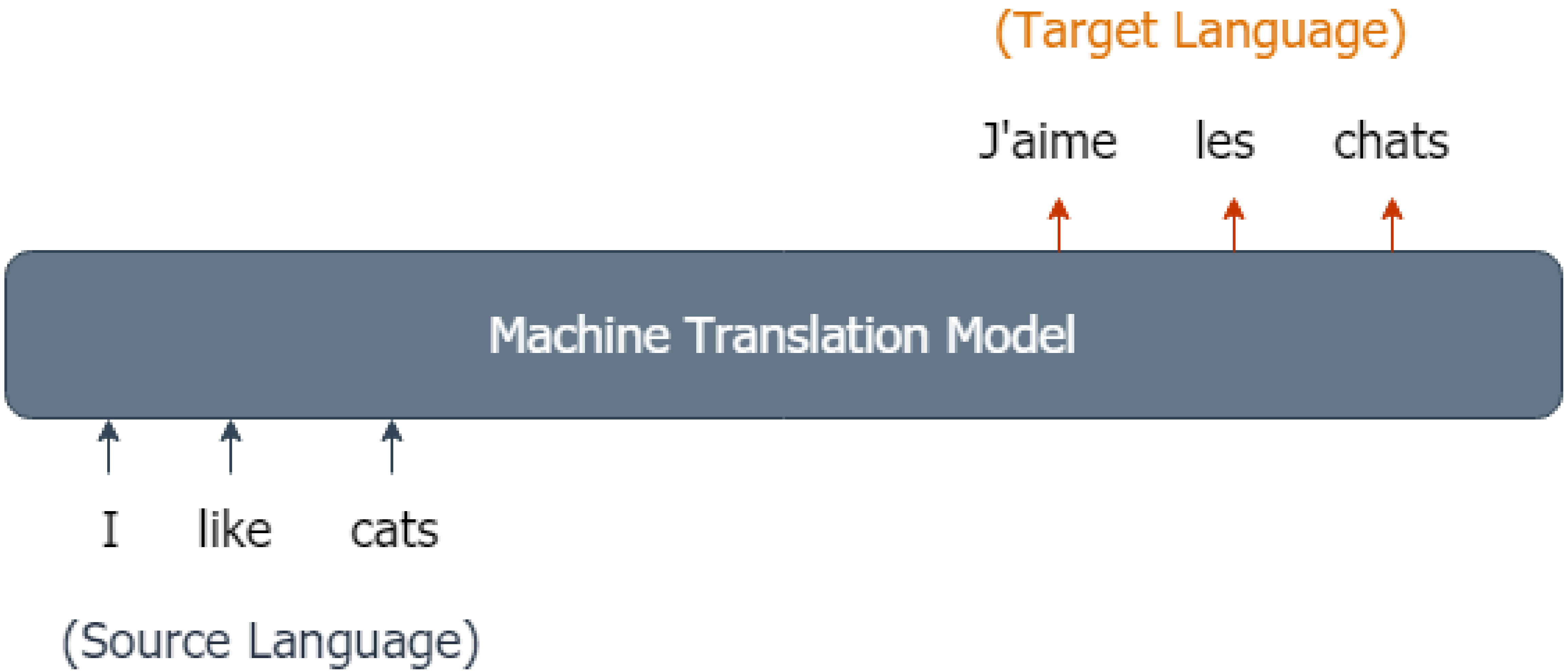


Machine translation - Overview



One-hot encoded vectors

- A vector of ones and zeros
- Vector length is determined by the size of the vocabulary
- Vocabulary - the collection of unique words in the dataset

I	1	0	0	0	0
like	0	1	0	0	0
cats	0	0	1	0	0

One-hot encoded vectors

A mapping containing words and their corresponding indices

```
word2index = {"I":0, "like": 1, "cats": 2}
```

Converting words to IDs or indices

```
words = ["I", "like", "cats"]
word_ids = [word2index[w] for w in words]
print(word_ids)
```

```
[0, 1, 2]
```

One-hot encoded vectors

One-hot encoding **without** specifying output vector length

```
onehot_1 = to_categorical(word_ids)
print([(w,ohe.tolist()) for w,ohe in zip(words, onehot_1)])
```

```
[('I', [1.0, 0.0, 0.0]), ('like', [0.0, 1.0, 0.0]), ('cats', [0.0, 0.0, 1.0])]
```

One-hot encoding **with** specifying output vector length

```
onehot_2 = to_categorical(word_ids, num_classes=5)
print([(w,ohe.tolist()) for w,ohe in zip(words, onehot_2)])
```

```
[('I', [1.0, 0.0, 0.0, 0.0, 0.0]), ('like', [0.0, 1.0, 0.0, 0.0, 0.0]),
('cats', [0.0, 0.0, 1.0, 0.0, 0.0])]
```

Let's practice!

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Encoder decoder architecture

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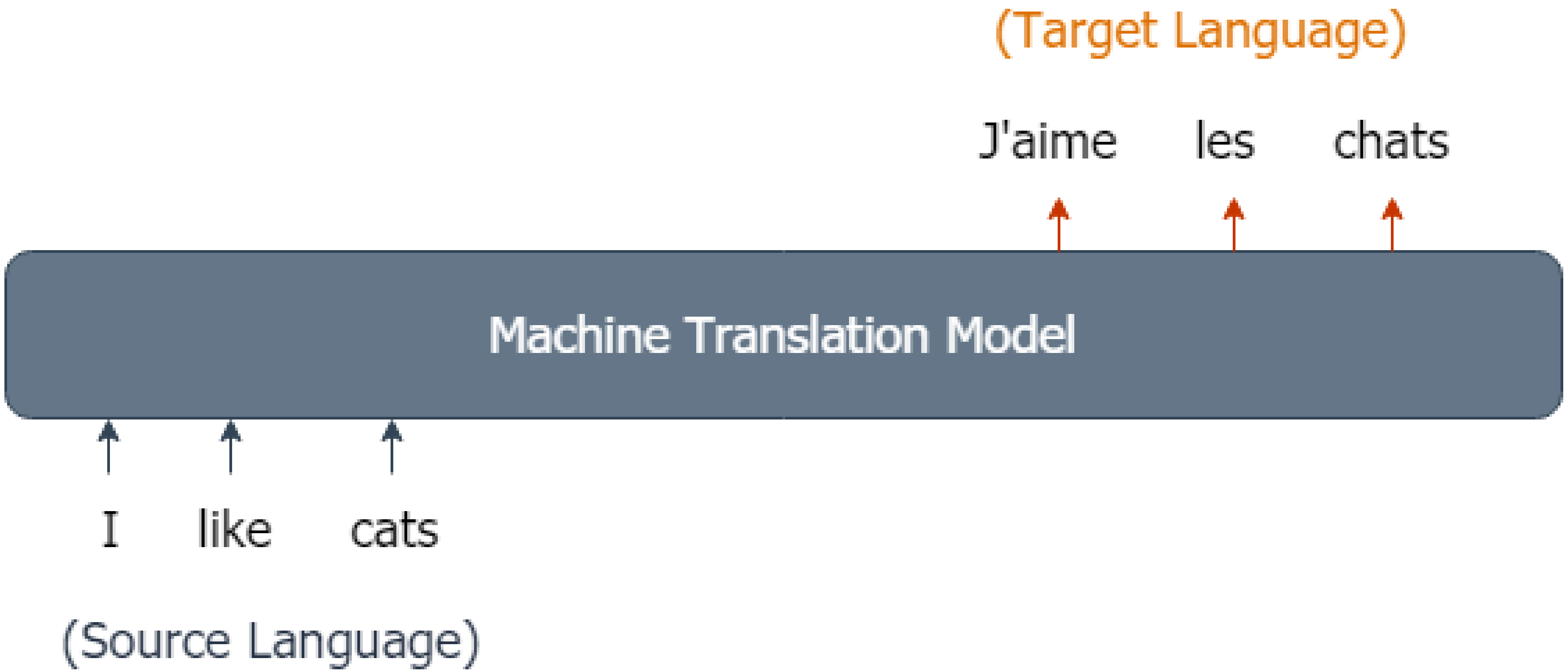
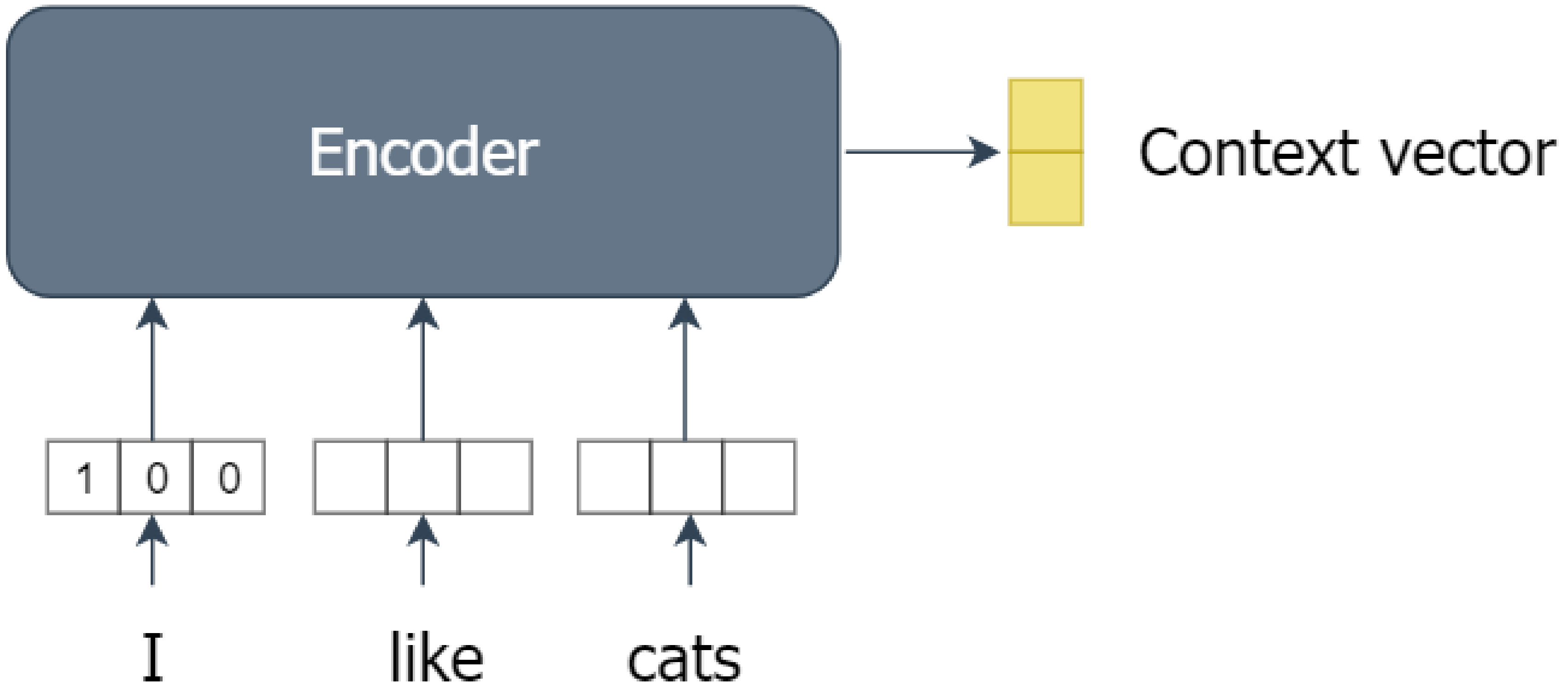
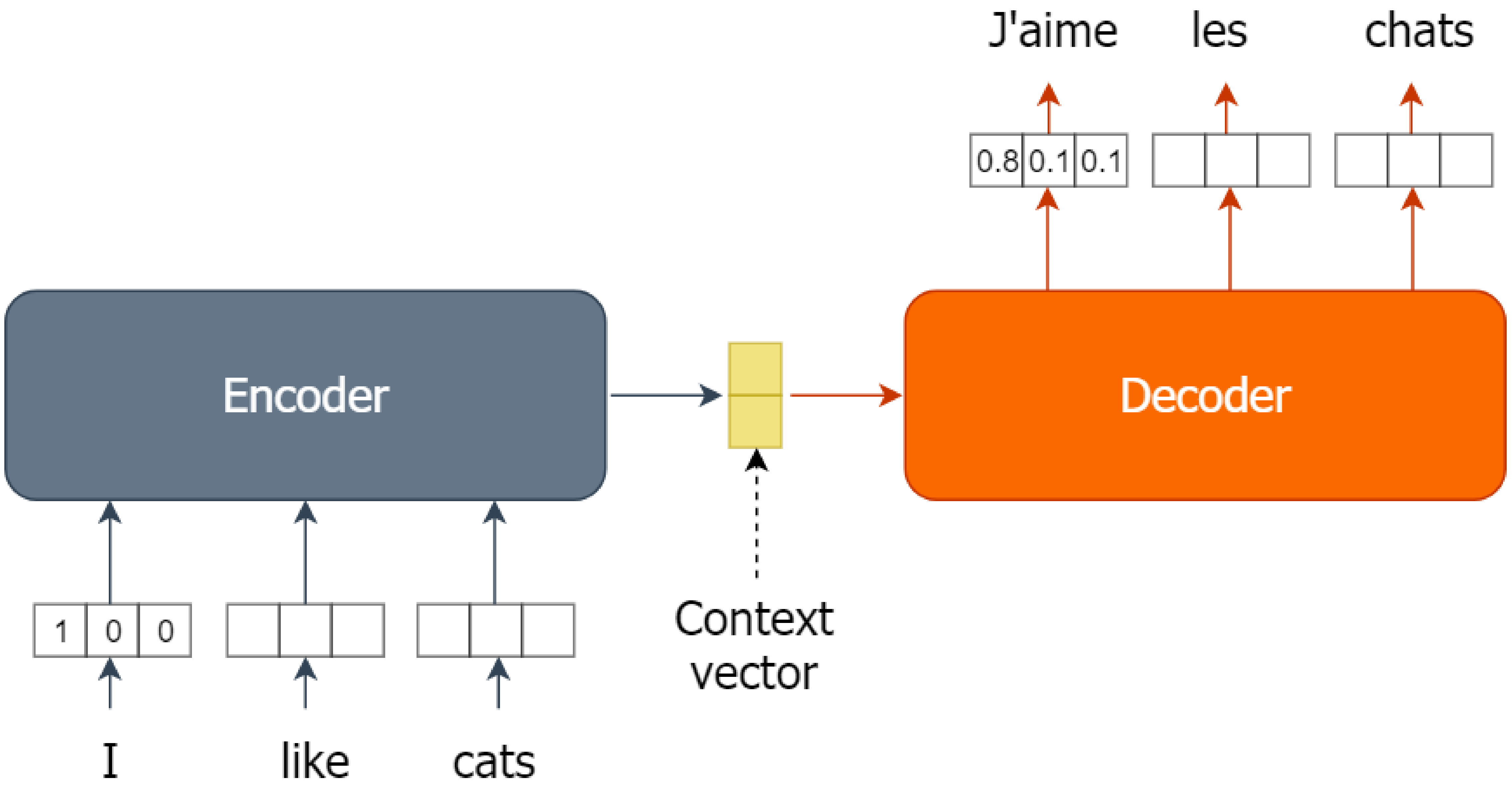
Encoder decoder model



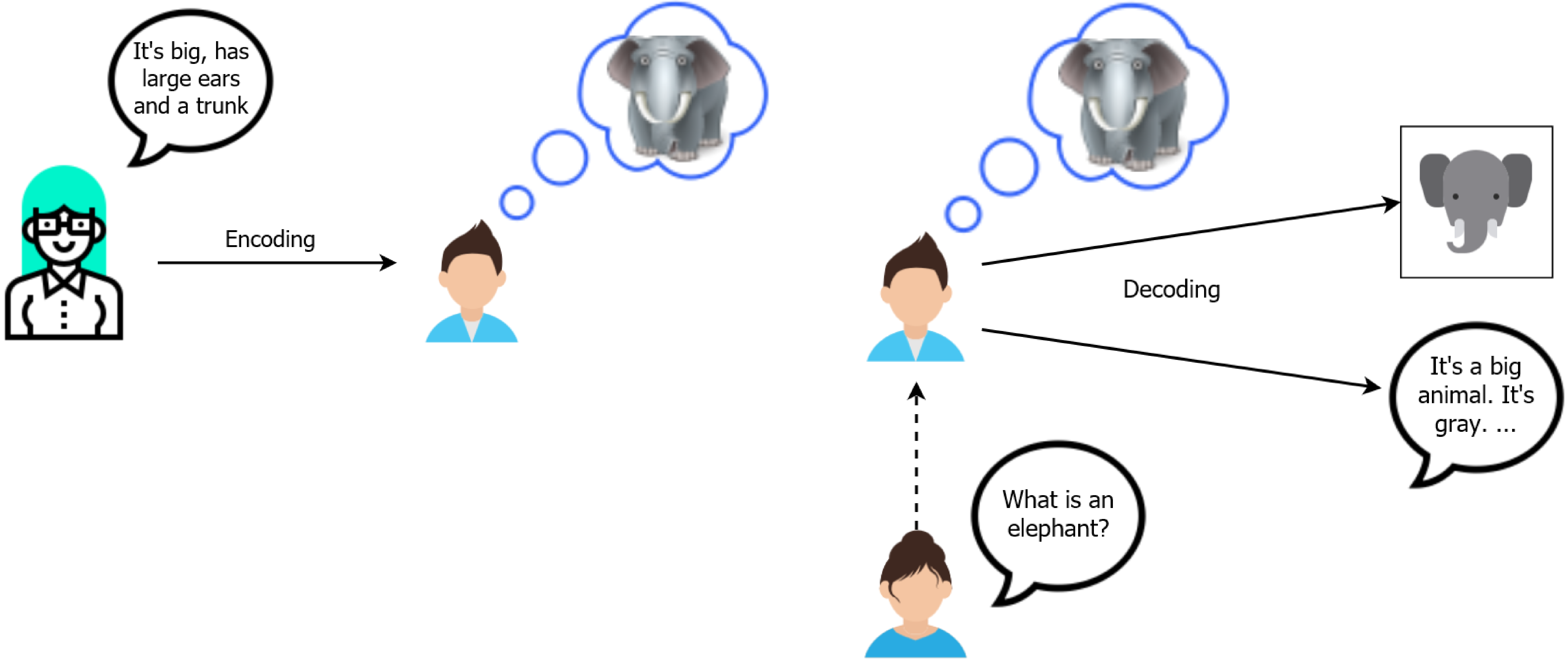
Encoder



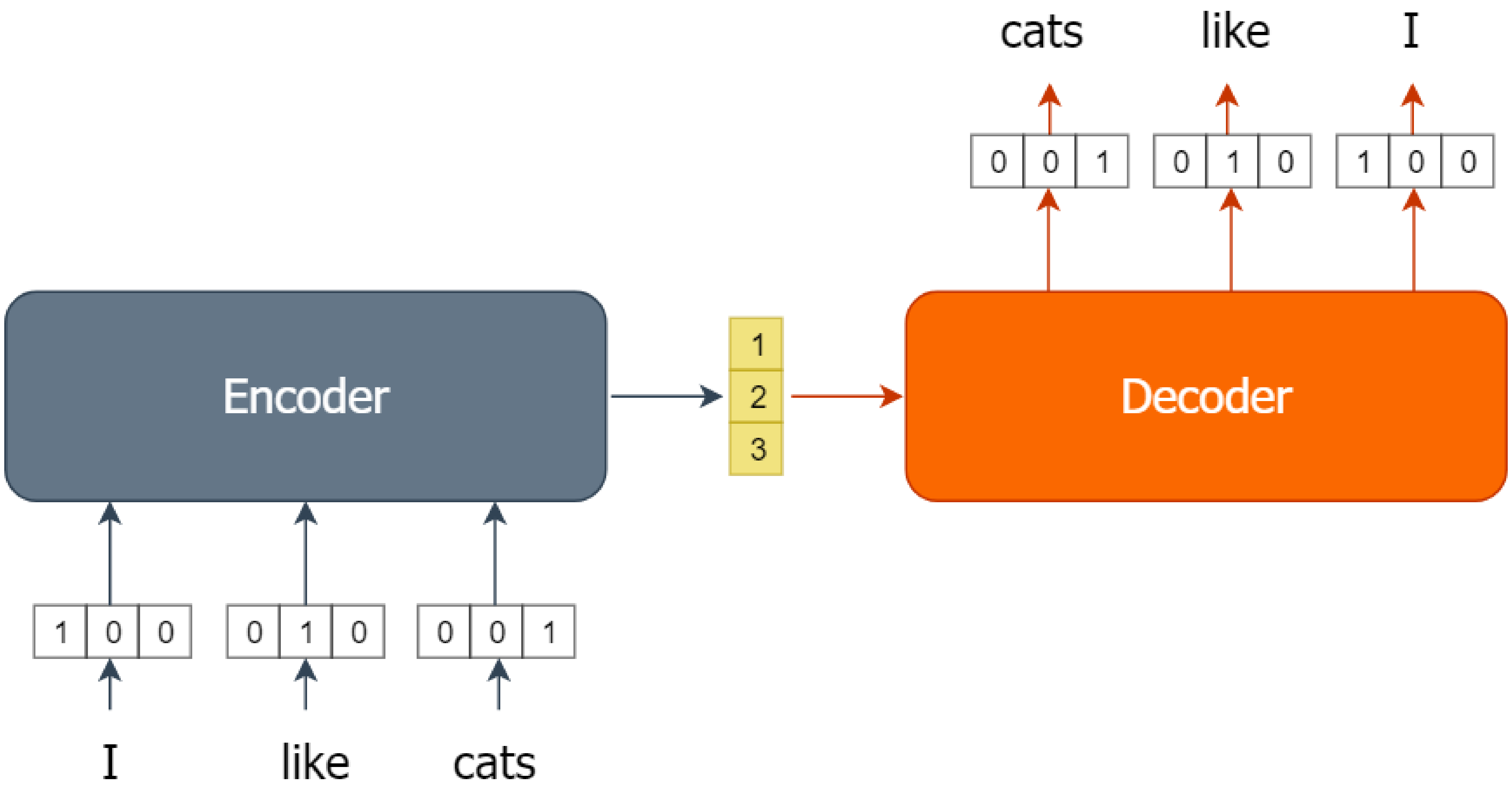
Encoder and Decoder



Analogy: Encoder decoder architecture



Reversing sentences - encoder decoder model



Writing the encoder

```
def words2onehot(word_list, word2index):
  word_ids = [word2index[w] for w in word_list]
  onehot = to_categorical(word_ids, 3)
  return onehot
```

```
def encoder(onehot):
  word_ids = np.argmax(onehot, axis=1)
  return word_ids
```

Writing the encoder

```
onehot = words2onehot(["I", "like", "cats"], word2index)
context = encoder(onehot)
print(context)
```

```
[0, 1, 2]
```

Writing the decoder

- Decoder: Word IDs ? Reverse the IDs ? one-hot vectors

```
def decoder(context_vector):
  word_ids_rev = context_vector[::-1]
  onehot_rev = to_categorical(word_ids_rev, 3)
  return onehot_rev
```

  - Helper function: convert one-hot vectors to human readable words

```
def onehot2words(onehot, index2word):
  ids = np.argmax(onehot, axis=1)
  return [index2word[id] for id in ids]
```

Writing the decoder

```
onehot_rev = decoder(context)
reversed_words = onehot2words(onehot_rev, index2word)

print(reversed_words)
```

```
['cats', 'like', 'I']
```

Let's practice!

MACHINE TRANSLATION IN PYTHON

Understanding sequential models

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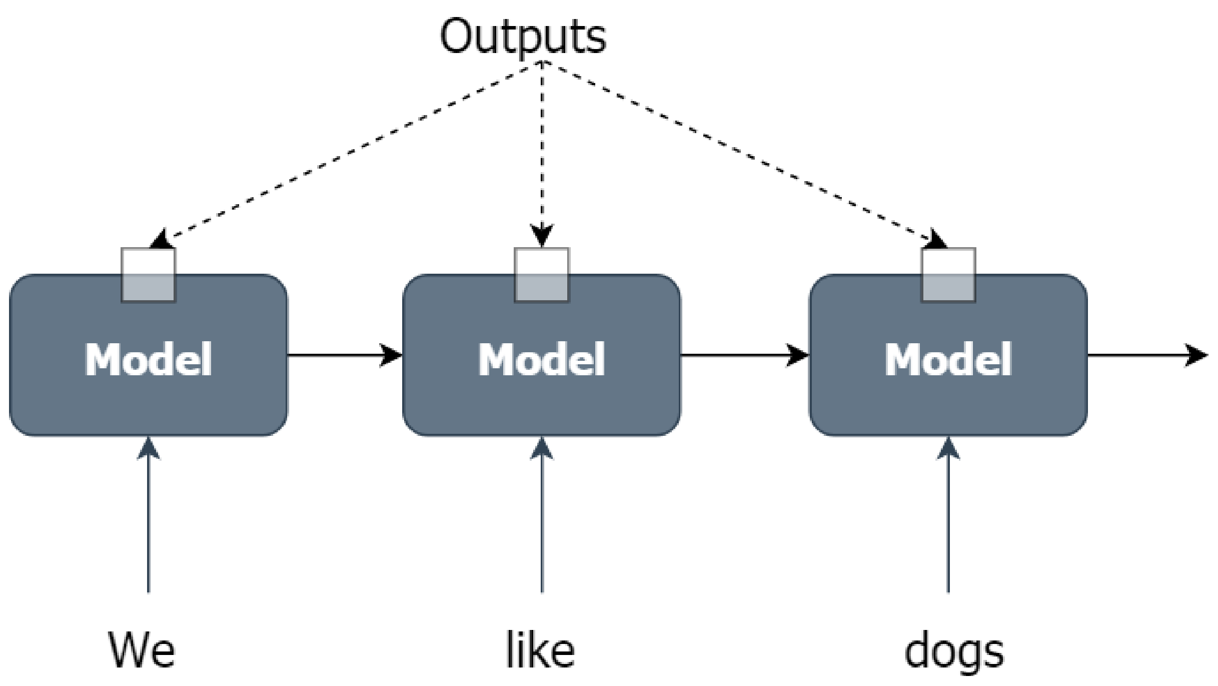
Time series inputs and sequential models

- A sentence is a time series input
  - Current word is affected by previous words
  - E.g. He went to the pool for a ....
- The encoder/decoder uses a machine learning model
  - Models that can learn from time-series inputs
  - Models are called **sequential models**

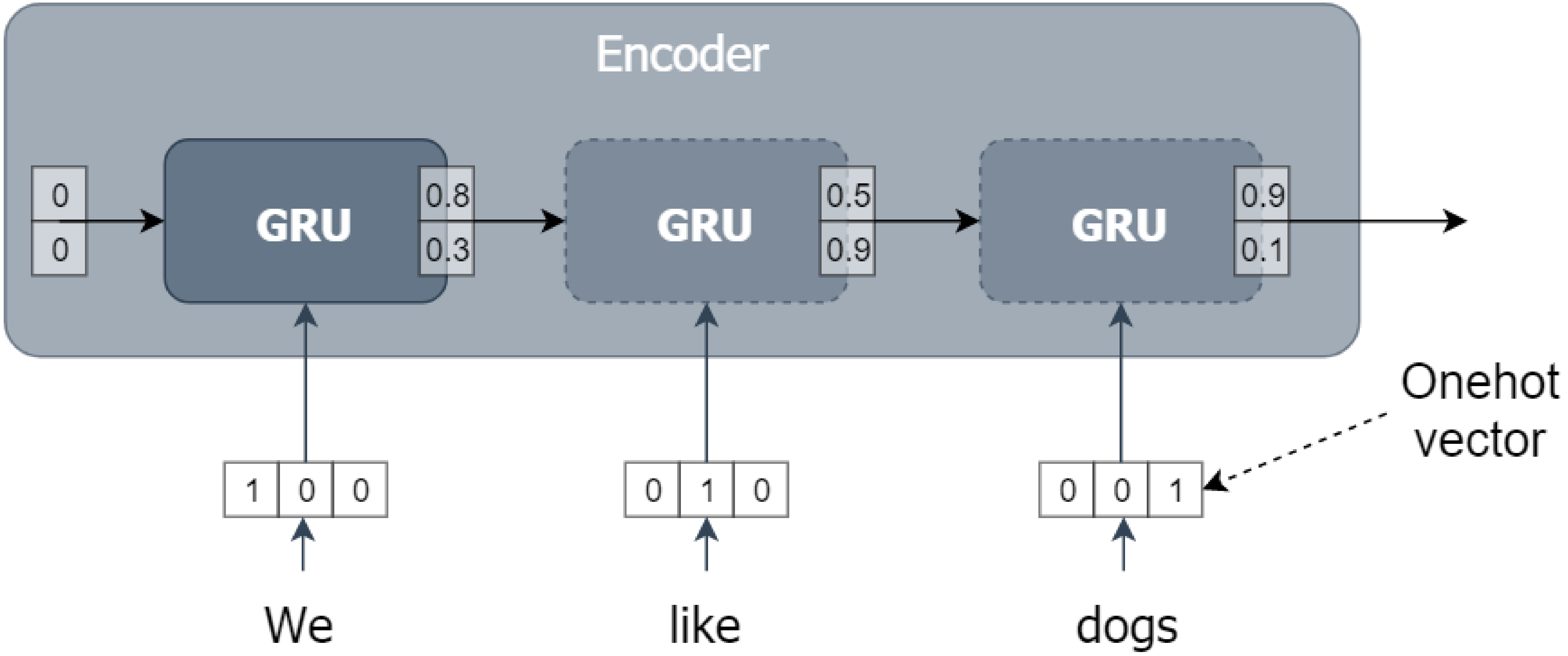
Sequential models

- Sequential models
  - Moves through the input while producing an output at each time step



Encoder as a sequential model

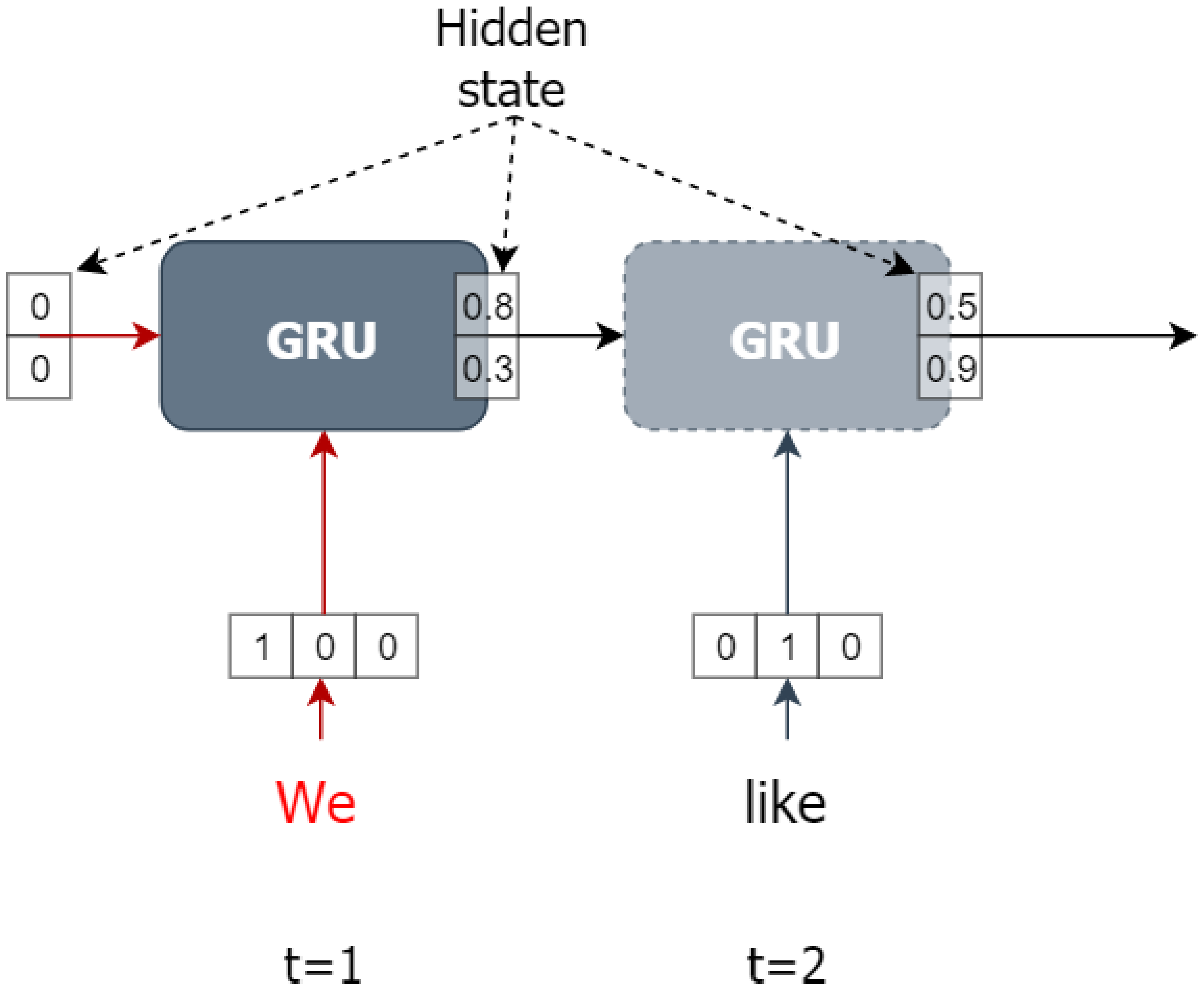
- GRU - Gated Recurrent Unit



Introduction to the GRU layer

At time step 1, the GRU layer,

- Consumes the input "We"
- Consumes the initial state (0,0)
- Outputs the new state (0.8, 0.3)

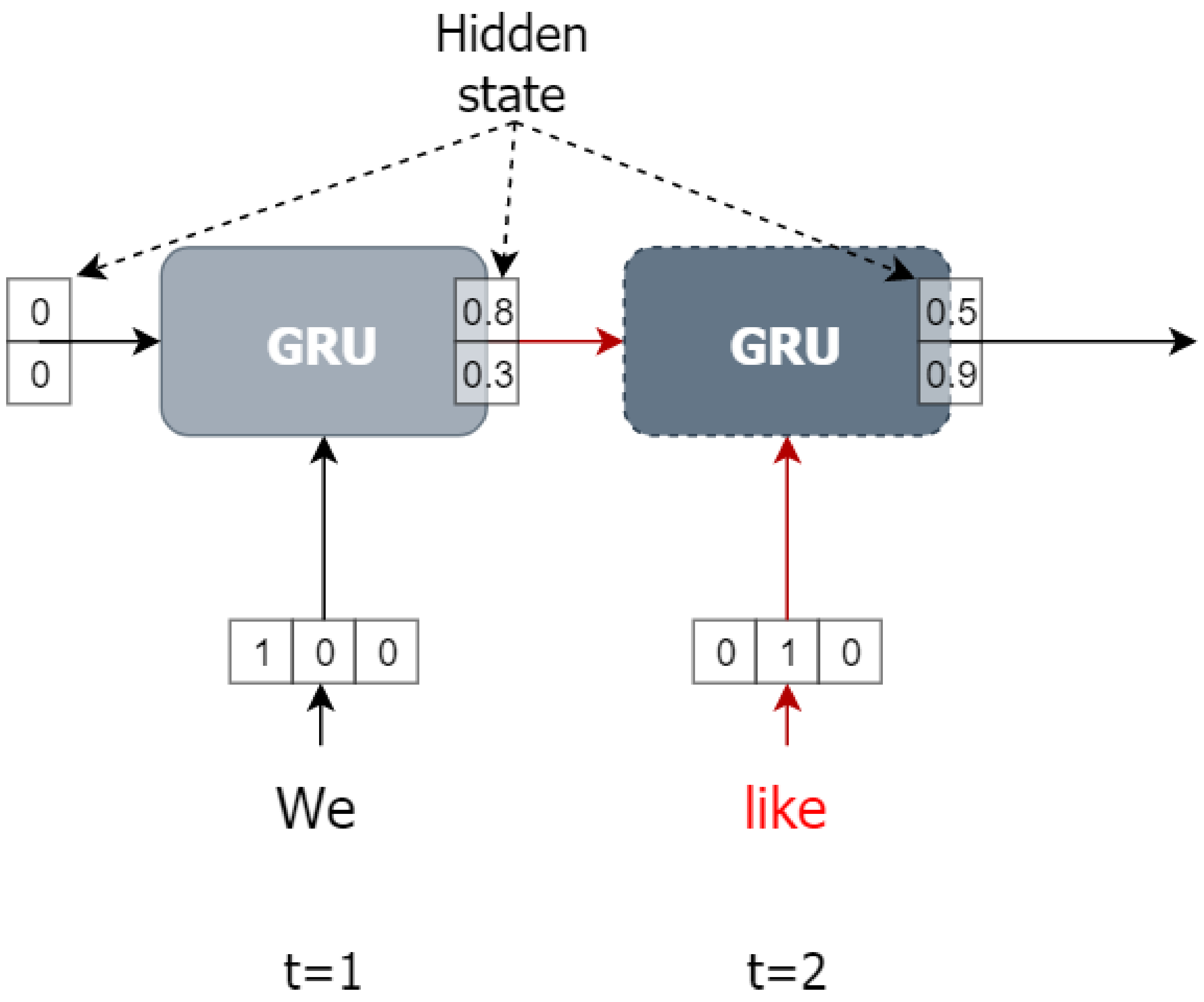


Introduction to GRU layer

At time step 2, the GRU layer,

- Consumes the input "like"
- Consumes the initial state (0.8,0.3)
- Outputs the new state (0.5, 0.9)

The hidden state represents "memory" of what the model has seen

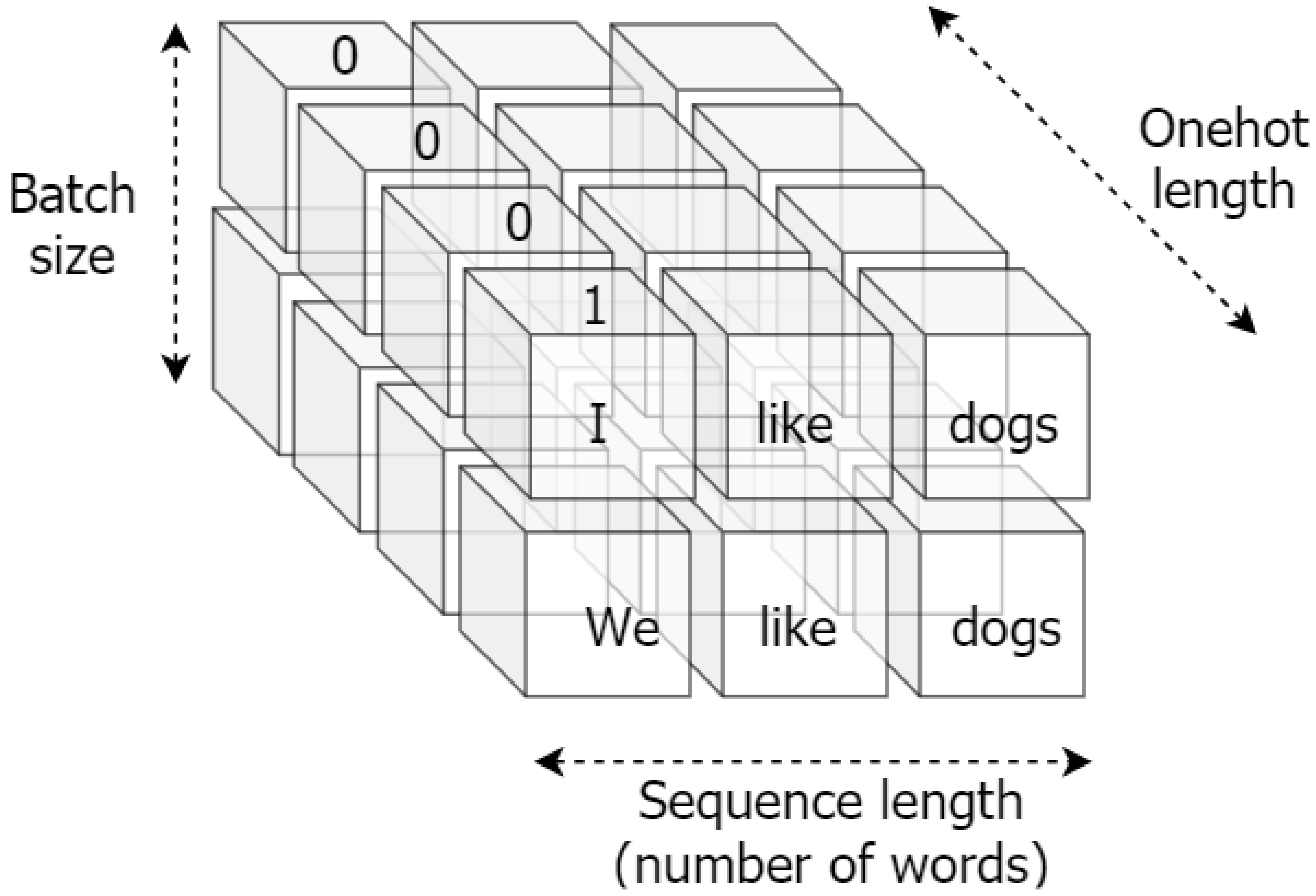


Keras (Functional API) refresher

- Keras has two important objects: `Layer` and `Model` objects.
- Input layer
  - `inp = keras.layers.Input(shape=(...))`
- Hidden layer
  - `layer = keras.layers.GRU(...)`
- Output
  - `out = layer(inp)`
- Model
  - `model = Model(inputs=inp, outputs=out)`

Understanding the shape of the data

- Sequential data is 3-dimensional
  - Batch dimension (e.g. batch = groups of sentences)
  - Time dimension - sequence length
  - Input dimension (e.g. onehot vector length)
- GRU model input shape
  - (Batch, Time, Input)
  - (batch size, sequence length, onehot length)



Implementing GRUs with Keras

Defining Keras layers

```
inp = keras.layers.Input(batch_shape=(2,3,4))
gru_out = keras.layers.GRU(10)(inp)
```

Defining a Keras model

```
model = keras.models.Model(inputs=inp, outputs=gru_out)
```

Implementing GRUs with Keras

Predicting with the Keras model

```
x = np.random.normal(size=(2,3,4))
y = model.predict(x)
print("shape (y) =", y.shape, "\ny = \n", y)
```

```
shape (y) = (2, 10)
y =
[[ 0.2576233   0.01215531  ... -0.32517594  0.4483121 ],
 [ 0.54189587 -0.63834655  ... -0.4339783   0.4043917 ]]
```

Implementing GRUs with Keras

A GRU that takes arbitrary number of samples in a batch

```
inp = keras.layers.Input(shape=(3,4))
gru_out = keras.layers.GRU(10)(inp)
model = keras.models.Model(inputs=inp, outputs=gru_out)
```

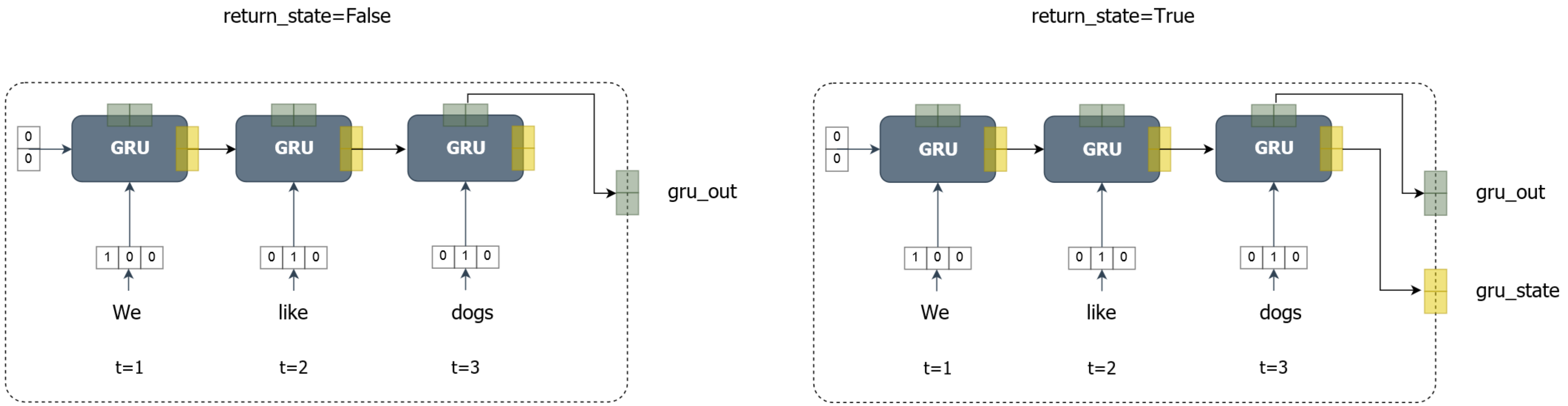
```
x = np.random.normal(size=(5,3,4))
y = model.predict(x)
print("y = \n", y)
```

```
y =
 [[-1.3941444e-02 -3.3123985e-02 ... 6.5081201e-02  1.1245312e-01]
 [ 1.1409521e-03  3.6983326e-01 ... -3.4610277e-01 -3.4792548e-01]
 [ 2.5911796e-01 -3.9517123e-01 ... 5.8505309e-01  3.6908010e-01]
 [-2.8727052e-01 -5.1150680e-02 ... -1.9637148e-01 -1.5587148e-01]
 [ 3.1303680e-01  2.3338445e-01 ... 9.1499090e-04 -2.0590121e-01]]
```

GRU layer's return_state argument

```
inp = keras.layers.Input(batch_shape=(2,3,4))
gru_out2, gru_state = keras.layers.GRU(10, return_state=True)(inp)
print("gru_out2.shape = ", gru_out2.shape)
print("gru_state.shape = ", gru_state.shape)
```

```
gru_out2.shape =  (2, 10)
gru_state.shape =  (2, 10)
```

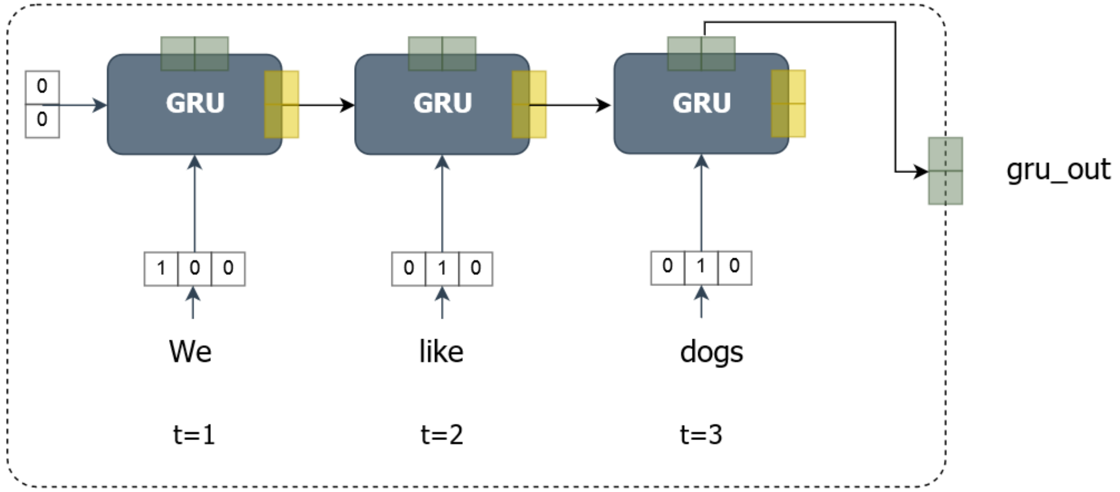


GRU layer's return_sequences argument

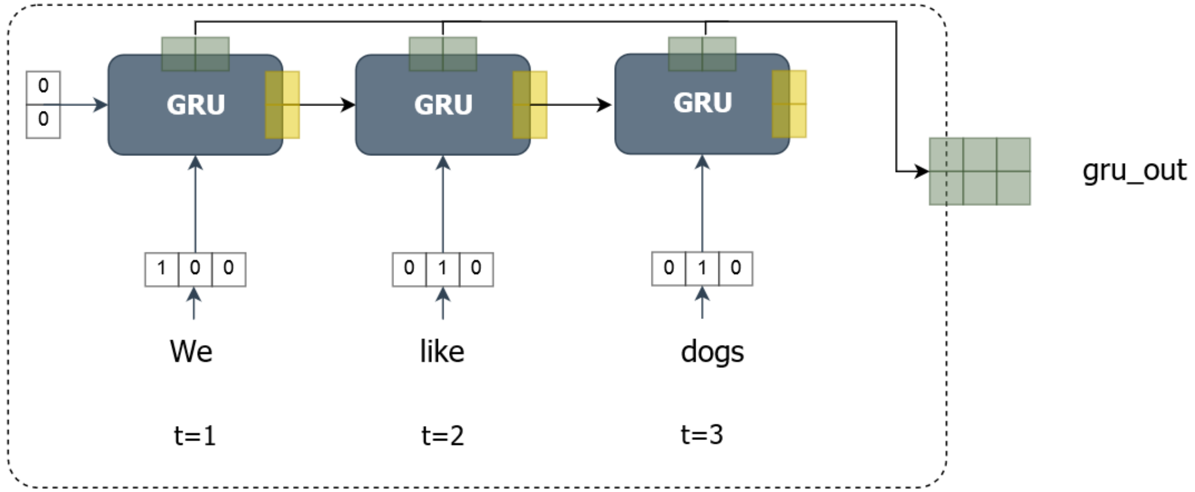
```
inp = keras.layers.Input(batch_shape=(2,3,4))
gru_out3 = keras.layers.GRU(10, return_sequences=True)(inp)
print("gru_out3.shape = ", gru_out2.shape)
```

```
gru_out3.shape =  (2, 3, 10)
```

return_sequences=False



return_sequences=True



Let's practice!

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