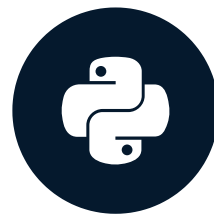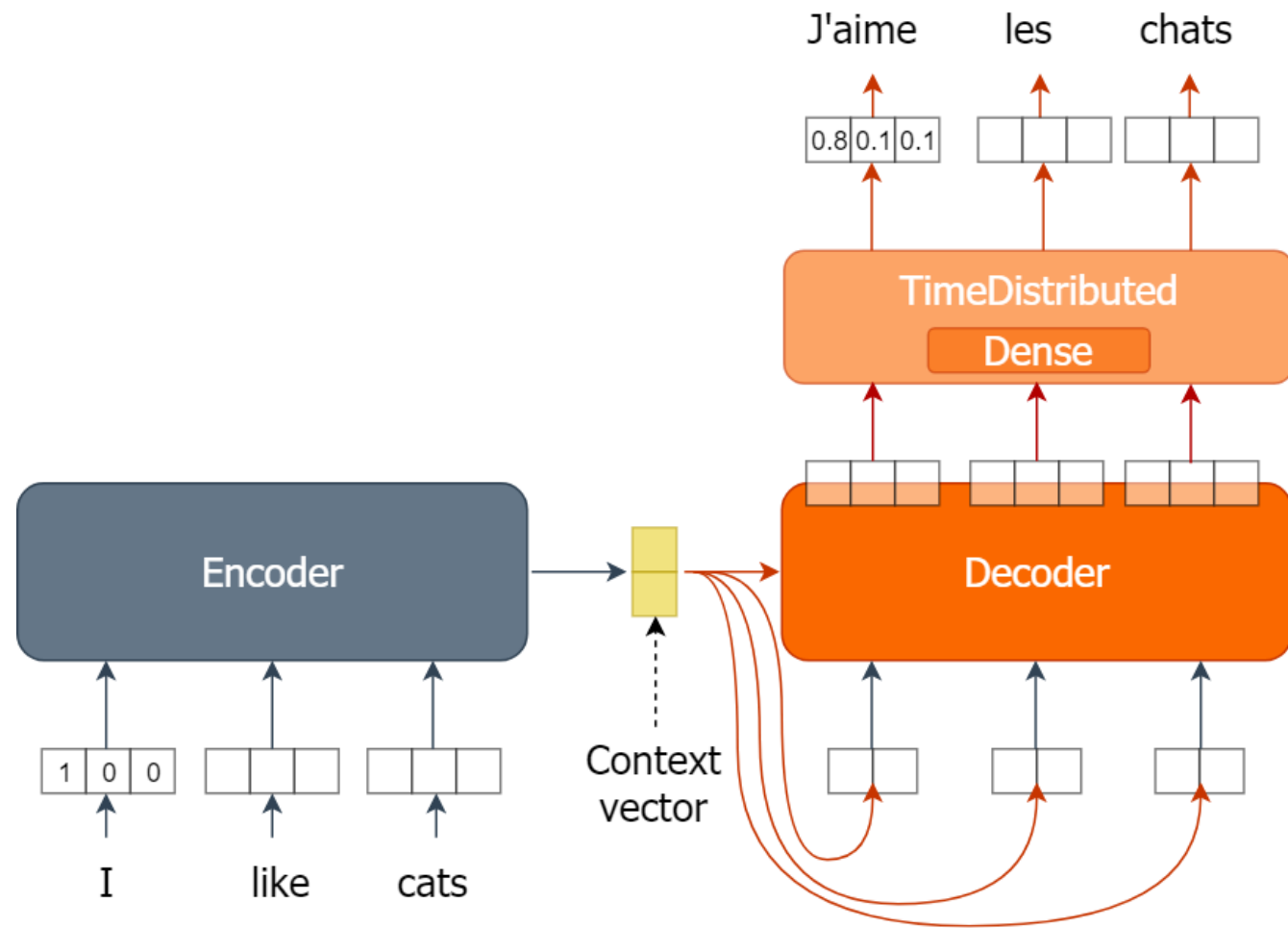# Introduction to Teacher Forcing

MACHINE TRANSLATION IN PYTHON

Thushan Ganegedara
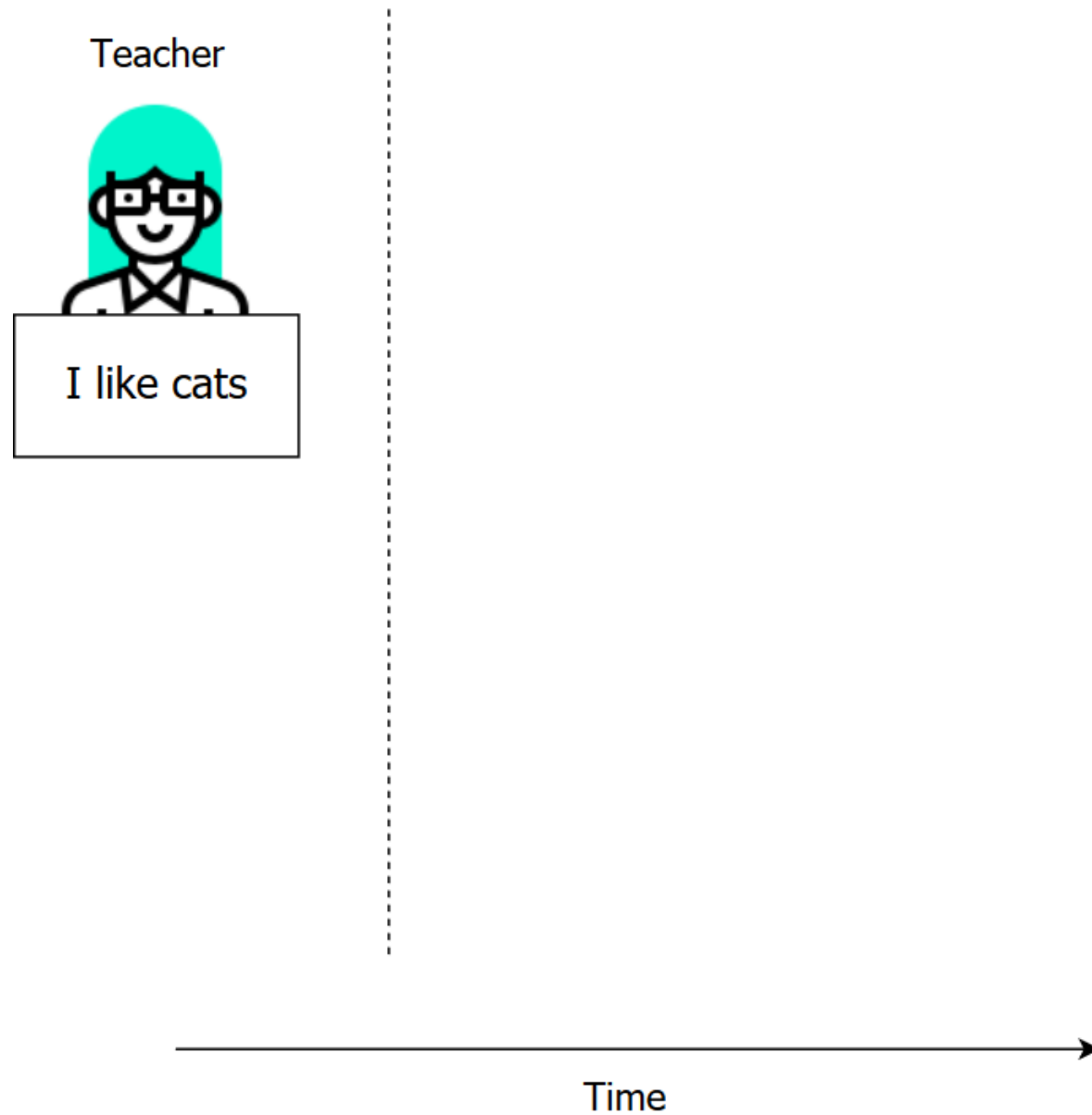Data Scientist and Author

The previous machine translator model
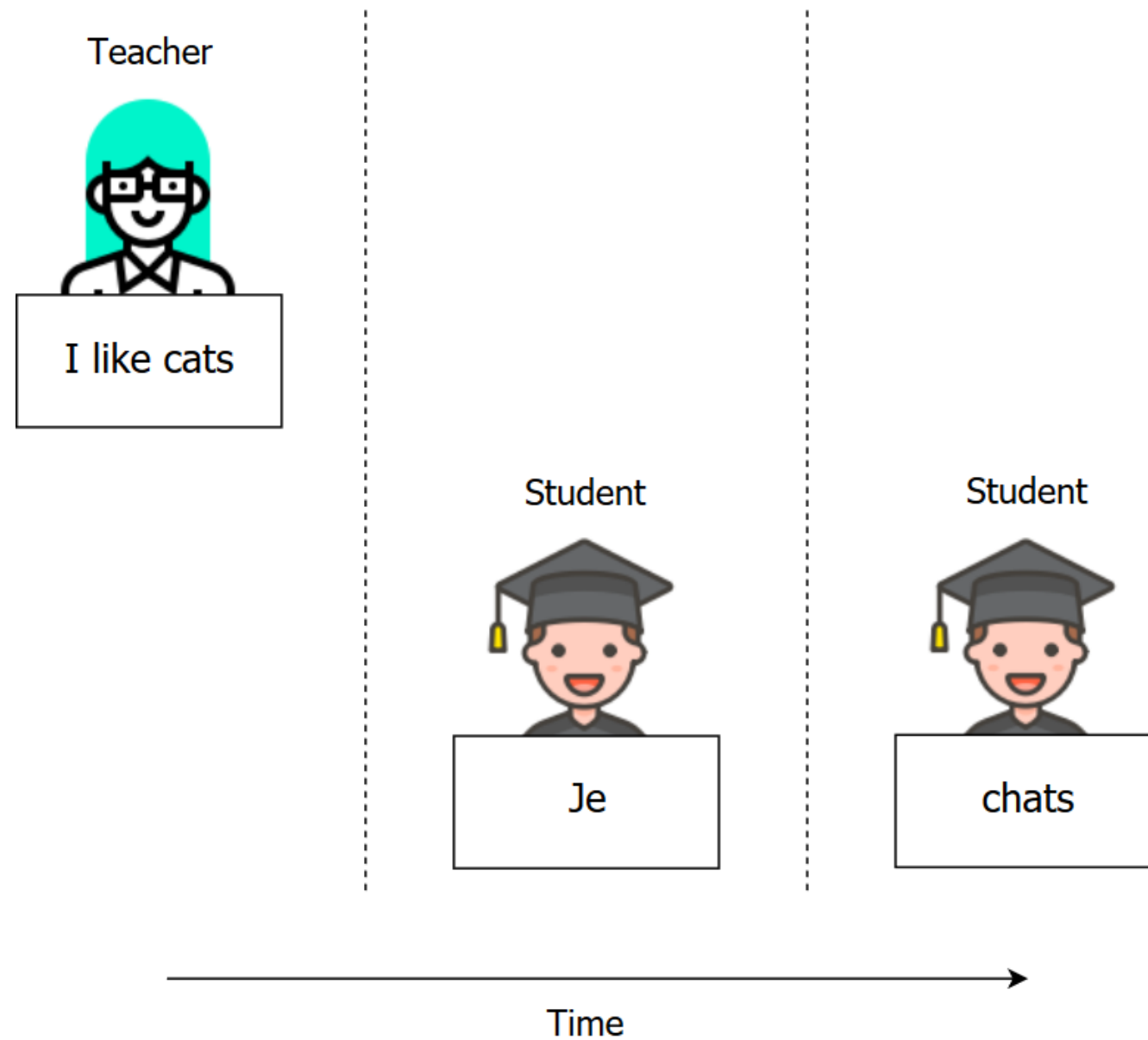
- The previous model

- Encoder GRU
  - Consumes English words
  - Outputs a context vector

- Decoder GRU
  - Consumes the context vector
  - Outputs a sequence of GRU outputs

- Decoder Prediction layer
  - Consumes the sequence of GRU outputs
  - Outputs prediction probabilities for French words

Analogy: Training without Teacher Forcing

Teacher

I like cats

Time

Analogy: Training without Teacher Forcing

Analogy: Training without Teacher Forcing

Teacher

I like cats

Student

Je

Student

chats

J'aime les chats

Time

Analogy: Training with Teacher Forcing

Teacher

I like cats

Time

Analogy: Training with Teacher Forcing

Teacher

I like cats

J'aime

Student

Je

Time
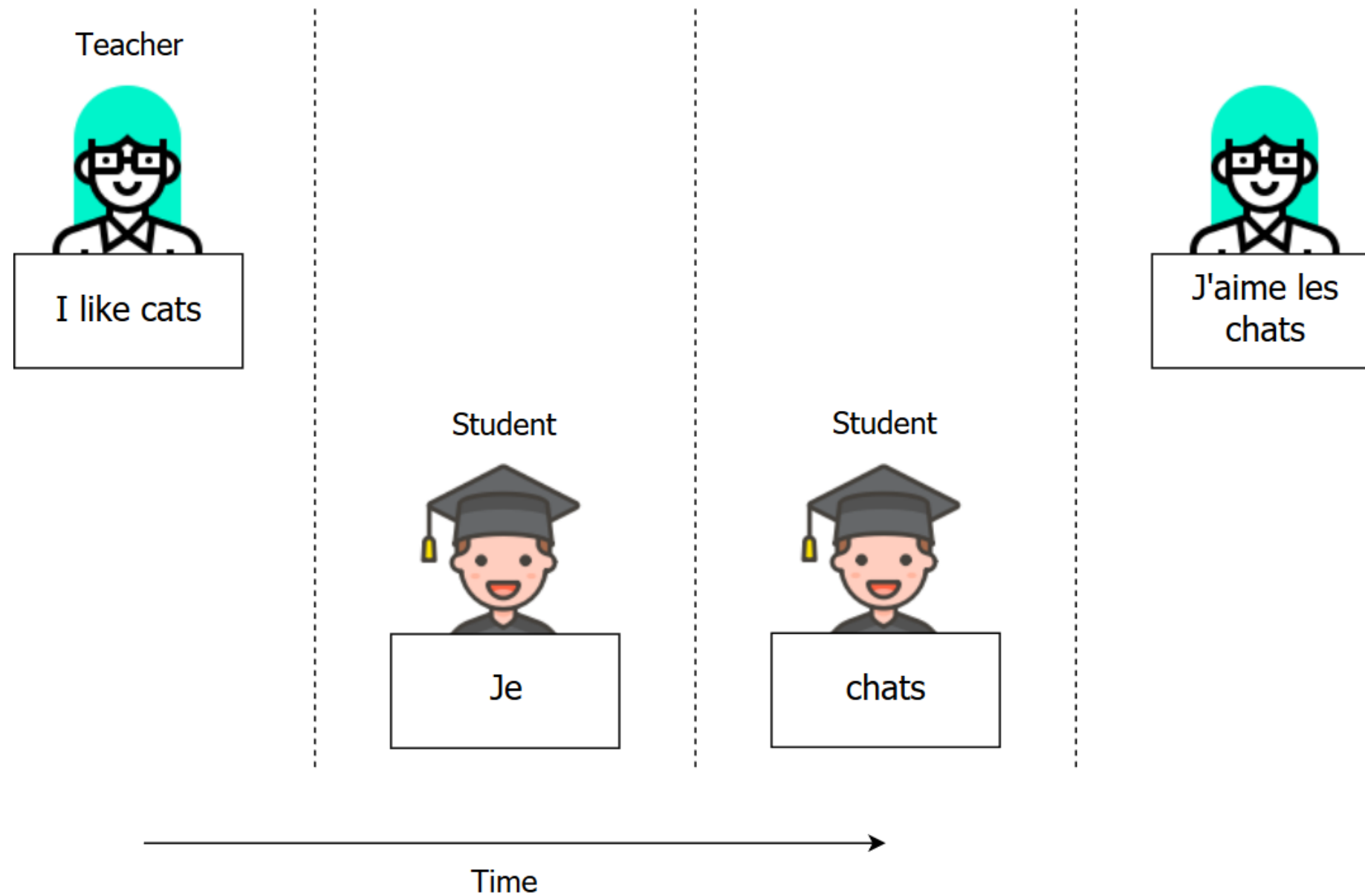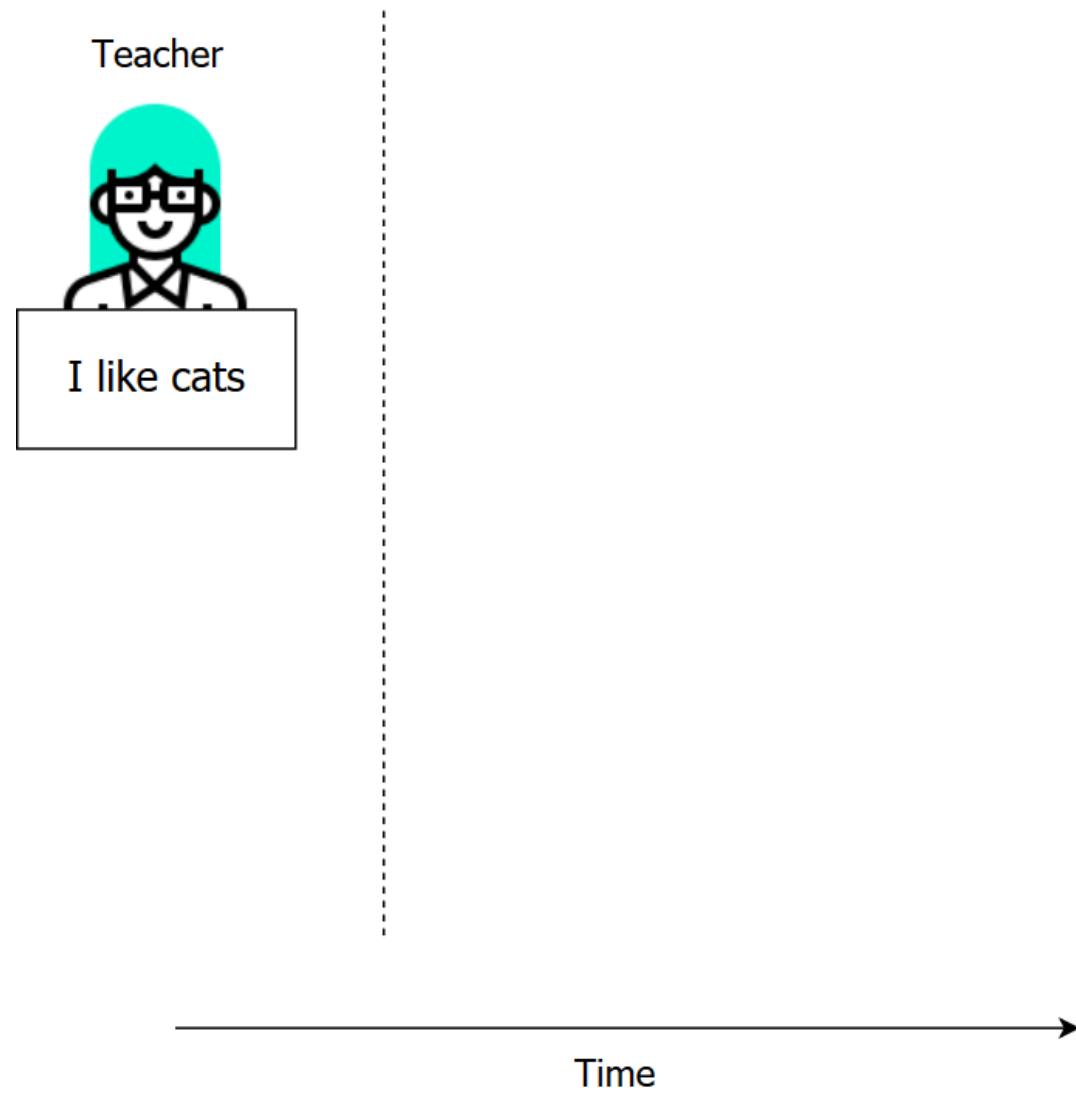
Analogy: Training with Teacher Forcing

Analogy: Training with Teacher Forcing

Teacher

| I like cats | | J'aime | | les | | chats |

Student

| | Je | | les | | chats | |

Time
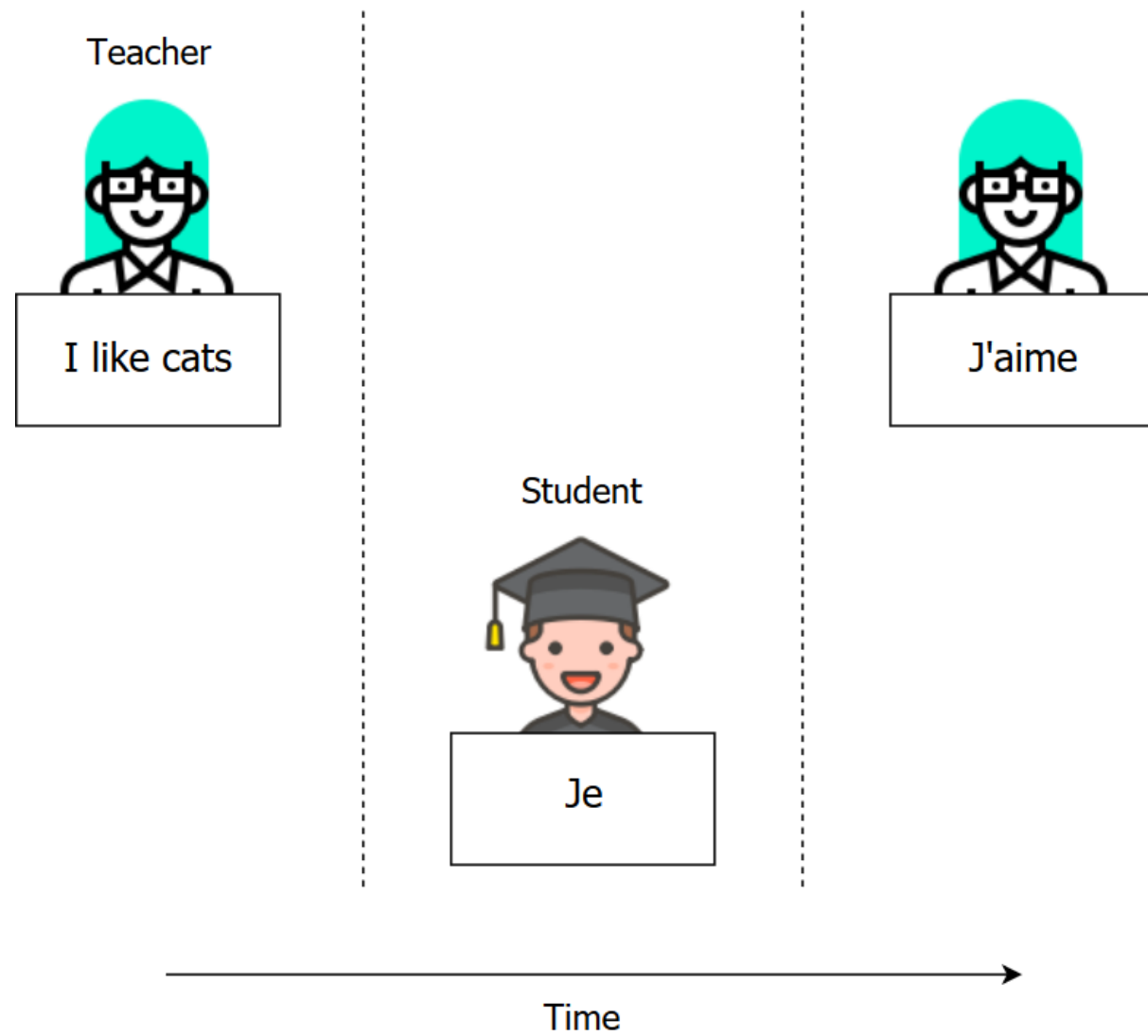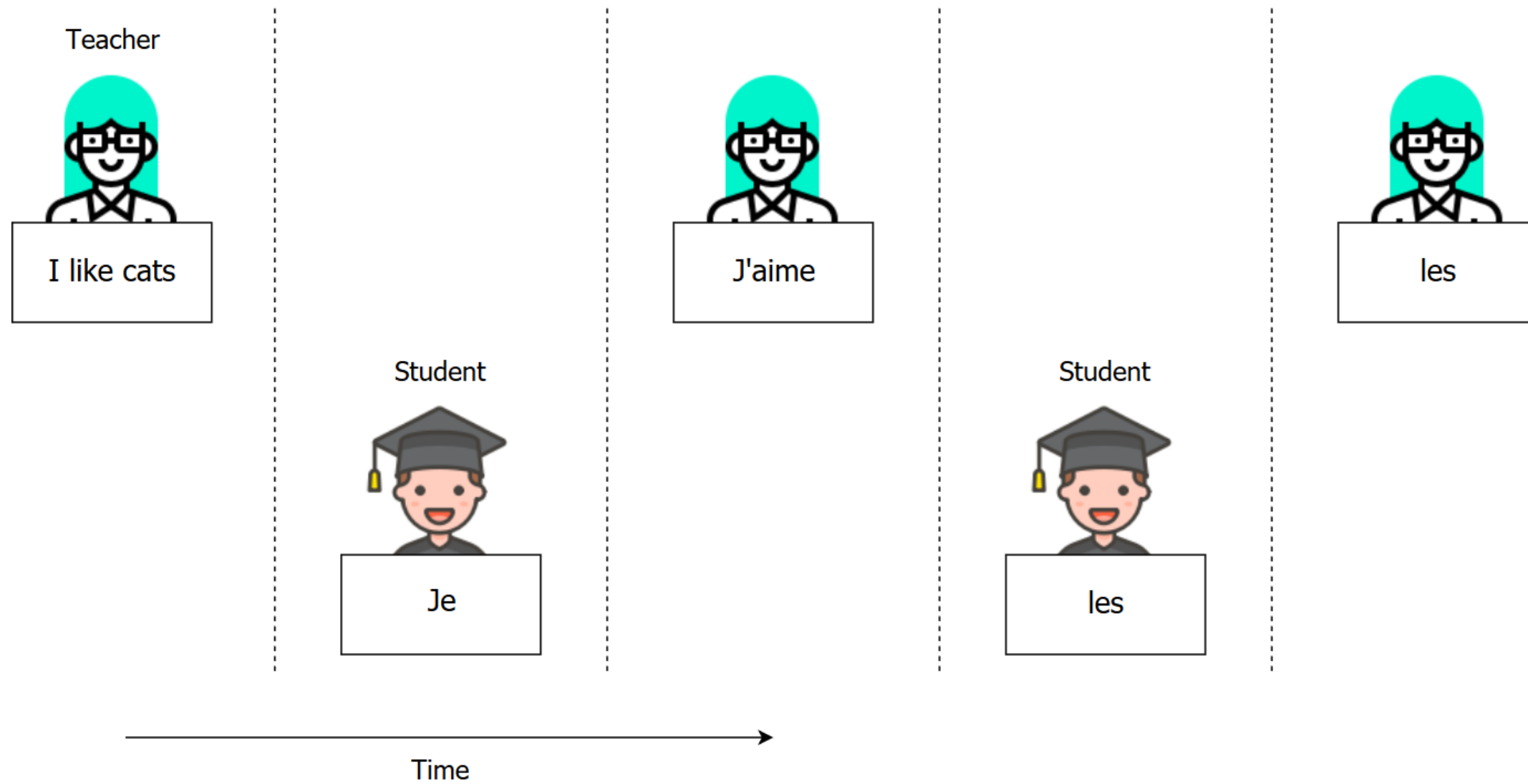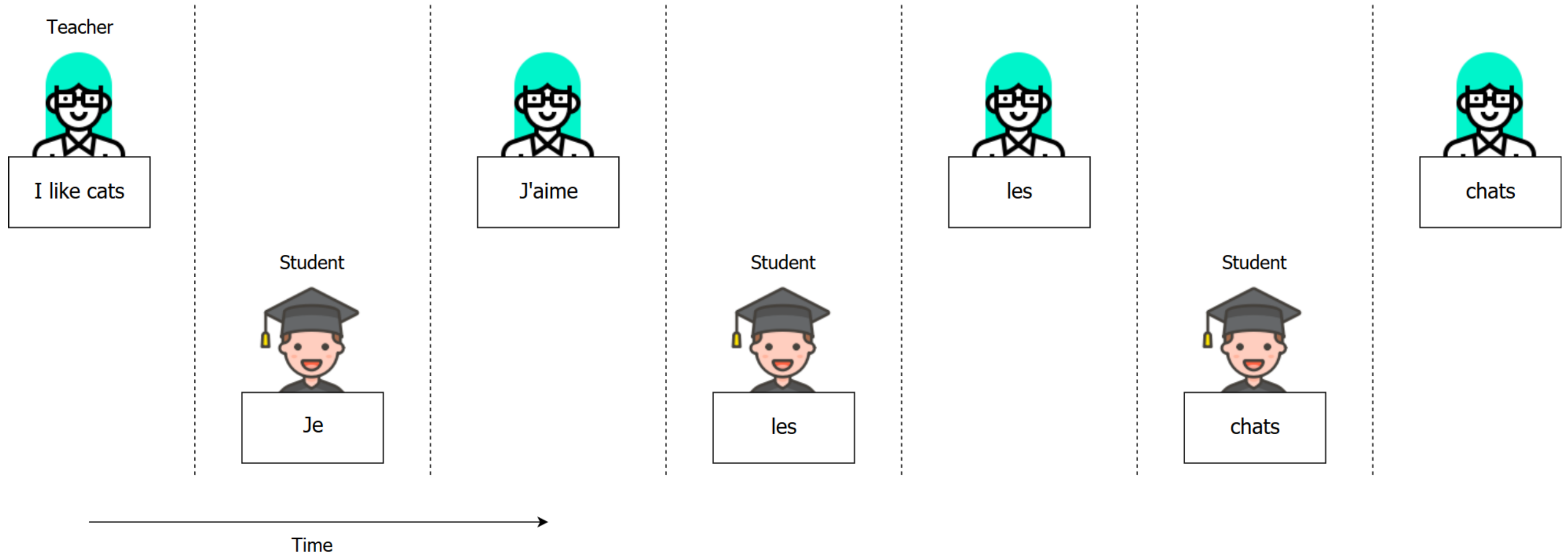
The previous machine translator model

- The previous model

- Teacher-forced model
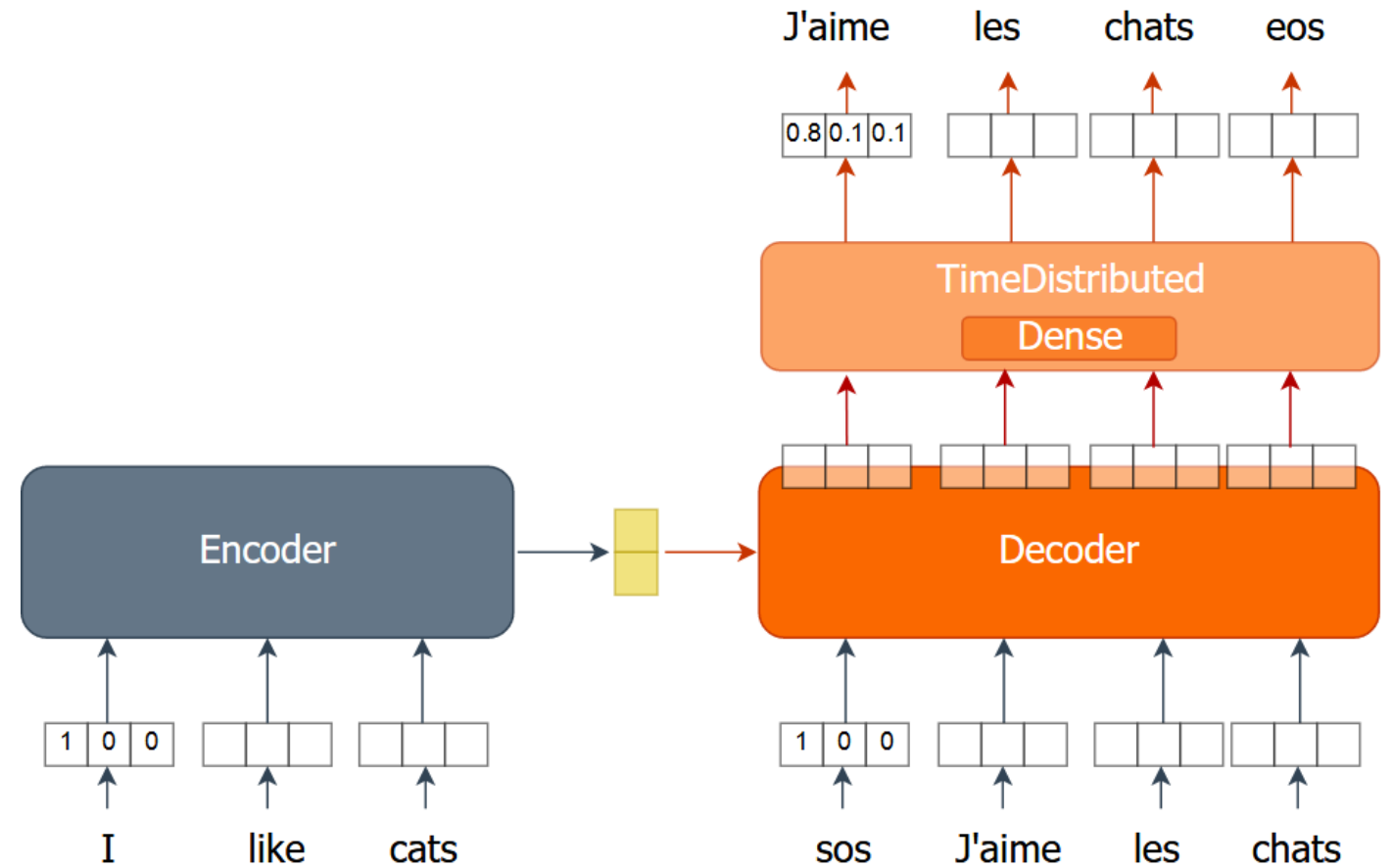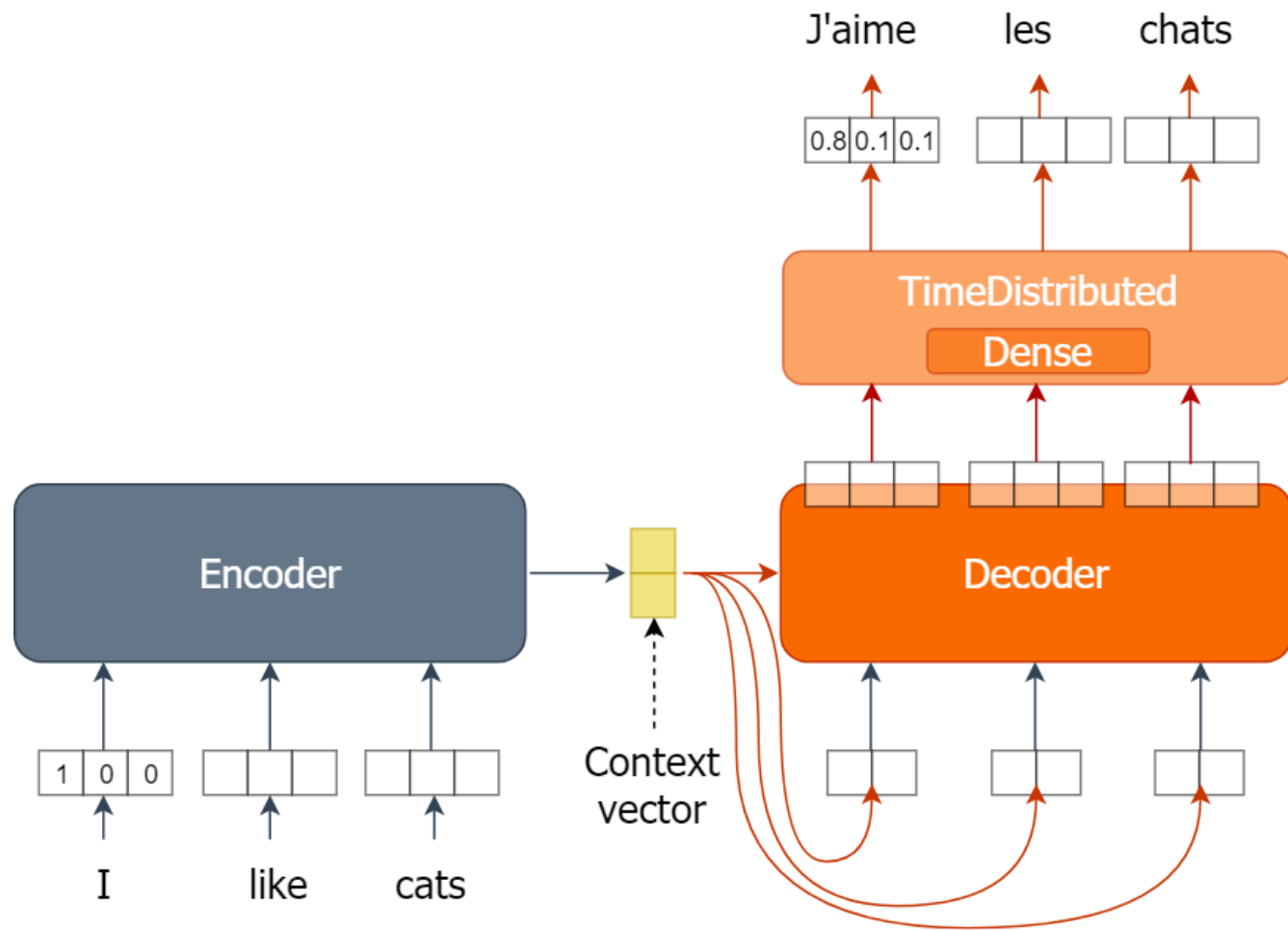
Implementing the model with Teacher Forcing

- Encoder

```
en_inputs = layers.Input(shape=(en_len, en_vocab))
en_gru = layers.GRU(hsize, return_state=True)
en_out, en_state = en_gru(en_inputs)
```

- Decoder GRU

```
de_inputs = layers.Input(shape=(fr_len-1, fr_vocab))
de_gru = layers.GRU(hsize, return_sequences=True)
de_out = de_gru(de_inputs, initial_state=en_state)
```

Inputs and outputs

- Encoder input - e.g. `I` , `like` , `dogs`

- Decoder input - e.g. `J'aime` , `les`

- Decoder output - e.g. `les` , `chiens`

Implementing the model with Teacher Forcing

- Encoder

```python
en_inputs = layers.Input(shape=(en_len, en_vocab))
en_gru = layers.GRU(hsize, return_state=True)
en_out, en_state = en_gru(en_inputs)
```
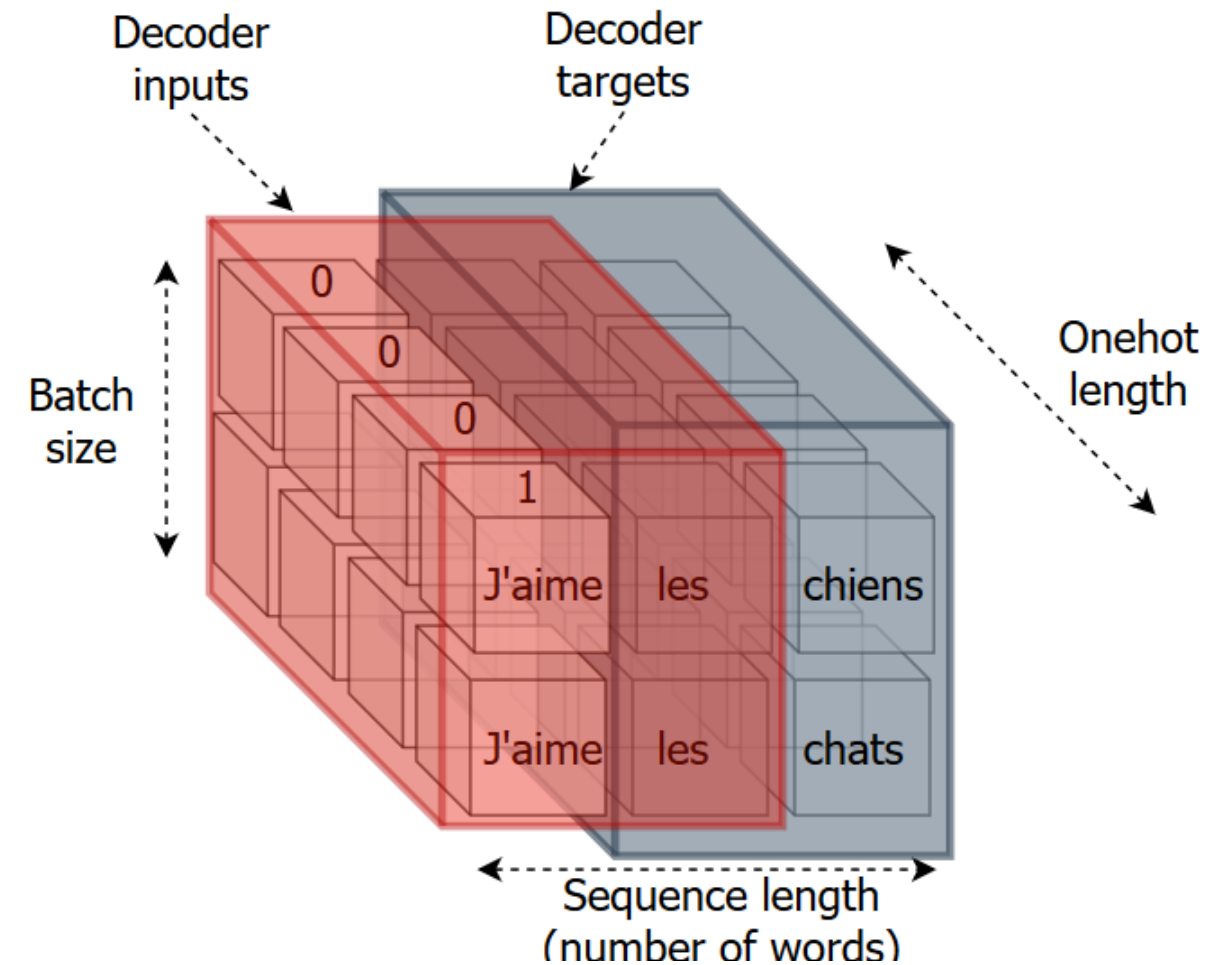
- Decoder GRU

```python
de_inputs = layers.Input(shape=(fr_len-1, fr_vocab))
de_gru = layers.GRU(hsize, return_sequences=True)
de_out = de_gru(de_inputs, initial_state=en_state)
```

- Decoder Prediction

```python
de_dense = layers.TimeDistributed(layers.Dense(fr_vocab, activation='softmax'))
de_pred = de_dense(de_out)
```

Compiling the model

```python
nmt_tf = Model(inputs=[en_inputs, de_inputs], outputs=de_pred)
nmt_tf.compile(optimizer='adam', loss="categorical_crossentropy", metrics=["acc"])
```

Preprocessing data

- Encoder
  - Inputs - All English words (onehot encoded)
    - `en_x = sents2seqs('source', en_text, onehot=True, reverse=True)`

- Decoder

```
de_xy = sents2seqs('target', fr_text, onehot=True)
```

  - Inputs - All French words except the last word (onehot encoded)
    - `de_x = de_xy[:,:-1,:]`
  - Outputs/Targets - All French words except the first word (onehot encoded)
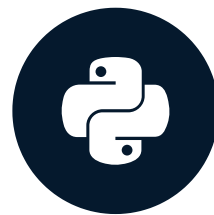   - `de_y = de_xy[:,1:,:]`

Let's practice!

MACHINE TRANSLATION IN PYTHON

Training the model with Teacher Forcing

MACHINE TRANSLATION IN PYTHON

Thushan Ganegedara
Data Scientist and Author

Model training in detail

- Model training requires:
  - A loss function (e.g. categorical crossentropy)

  - An optimizer (e.g. Adam)

Model training in detail

- To compute loss, following items are required:
  - Probabilistic predictions generated using inputs (`[batch_size, seq_len, vocab_size]`)
    - e.g. `[[0.11,...,0.81,0.04], [0.05,...,0.01, 0.93], ..., [0.78,..., 0.03,0.01]]`

  - Actual onehot encoded French targets (`[batch_size, seq_len, vocab_size]`)
    - e.g. `[[0, ..., 1, 0], [0, ..., 0, 1],..., [0, ..., 1, 0]]`

  - Crossentropy: difference between the targets and predicted words

- The loss is passed to an optimizer which will change the model parameters to minimize the loss

Training the model with Teacher Forcing

```python
n_epochs, bsize = 3, 250
for ei in range(n_epochs):
  for i in range(0,data_size,bsize):
    # Encoder inputs, decoder inputs and outputs
    en_x = sents2seqs('source', en_text[i:i+bsize], onehot=True, reverse=True)
    de_xy = sents2seqs('target', fr_text[i:i+bsize], onehot=True)
    # Separating decoder inputs and outputs
    de_x = de_xy[:,:-1,:]
    de_y = de_xy[:,1:,:]
    # Training and evaulating on a single batch
    nmt_tf.train_on_batch([en_x,de_x], de_y)
    res = nmt_tf.evaluate([en_x,de_x], de_y, batch_size=bsize, verbose=0)
    print("{} => Train Loss:{}, Train Acc: {}".format(ei+1,res[0], res[1]*100.0))
```

Array slicing in detail

```
de_x = de_xy[:,:-1,:]
de_y = de_xy[:,1:,:]
```
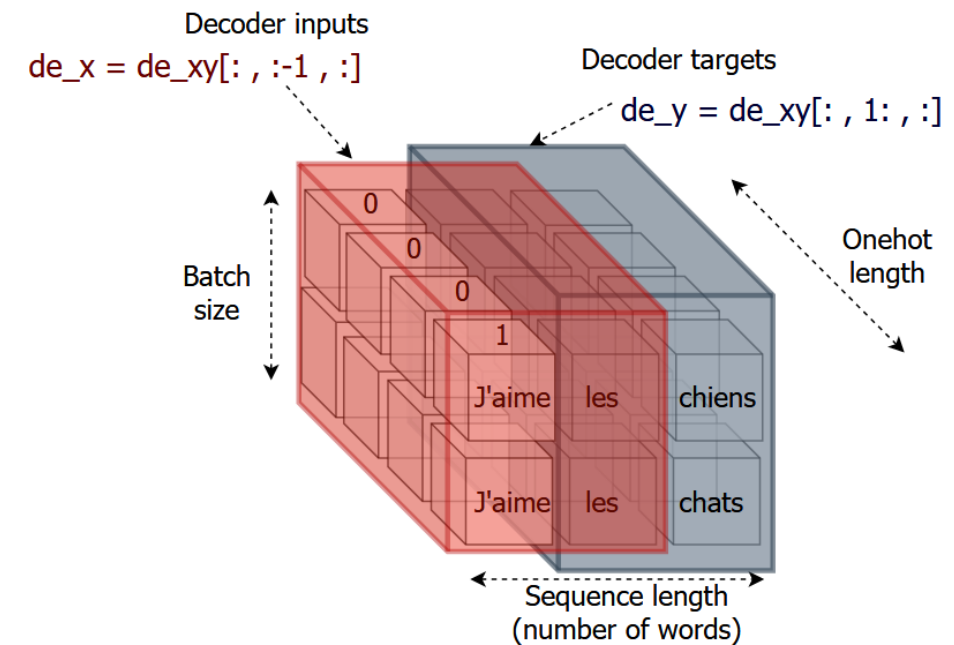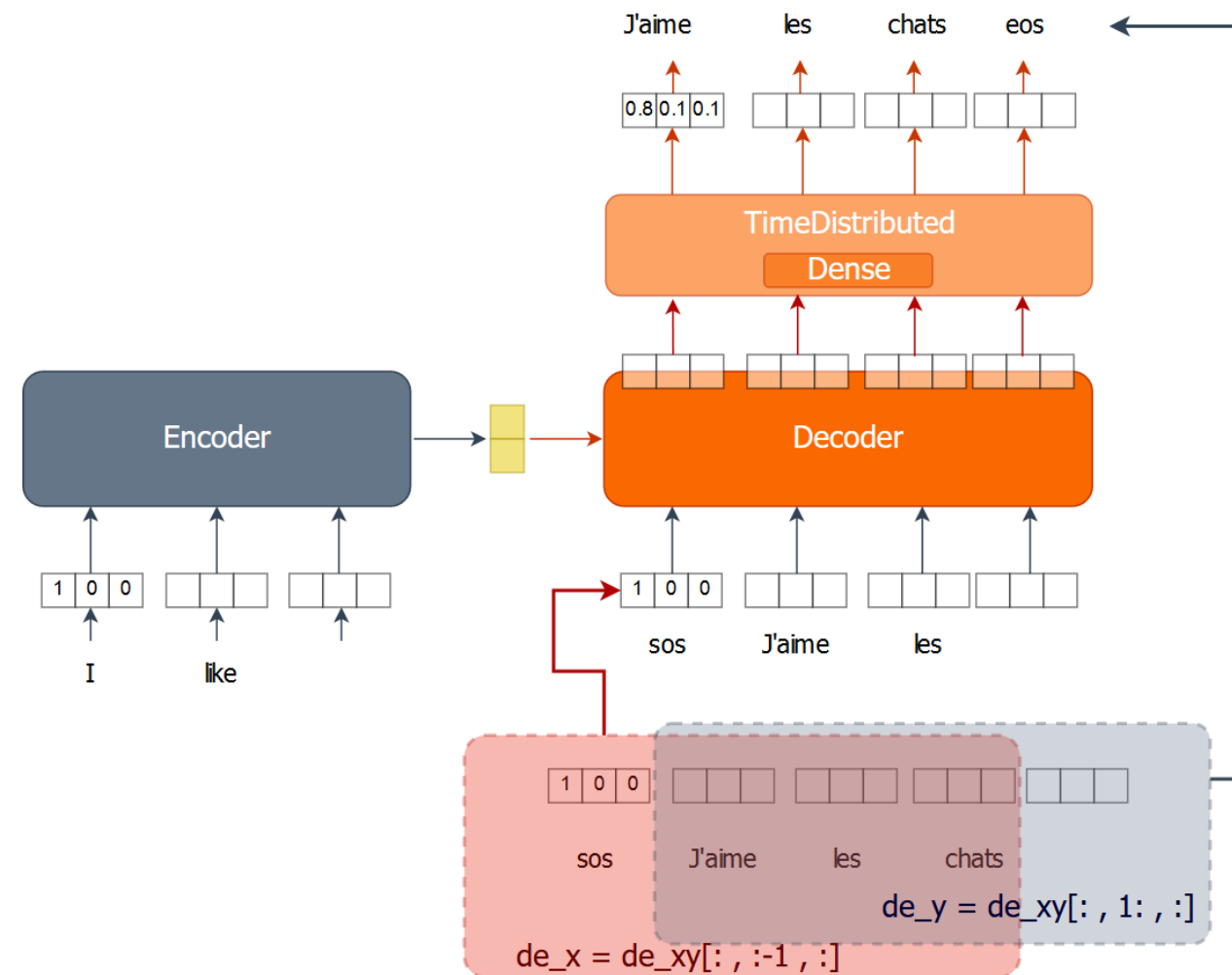
Creating training and validation data

```python
train_size, valid_size = 800, 200
# Creating data indices
inds = np.arange(len(en_text))
np.random.shuffle(inds)

# Separating train and valid indices
train_inds = inds[:train_size]
valid_inds = inds[train_size:train_size+valid_size]

# Extracting train and valid data
tr_en = [en_text[ti] for ti in train_inds]
tr_fr = [fr_text[ti] for ti in train_inds]

v_en = [en_text[vi] for vi in valid_inds]
v_fr = [fr_text[vi] for vi in valid_inds]
print('Training (EN):\n', tr_en[:2], '\nTraining (FR):\n', tr_fr[:2])
print('\nValid (EN):\n', tr_en[:2], '\nValid (FR):\n', tr_fr[:2])
```

Training with validation

```python
for ei in range(n_epochs):
  for i in range(0,train_size,bsize):
    en_x = sents2seqs('source', tr_en[i:i+bsize], onehot=True, reverse=True)
    de_xy = sents2seqs('target', tr_fr[i:i+bsize], onehot=True)
    de_x, de_y = de_xy[:,:-1,:], de_xy[:,1:,:]
    nmt_tf.train_on_batch([en_x, de_x], de_y)
  v_en_x = sents2seqs('source', v_en, onehot=True, reverse=True)
  v_de_xy = sents2seqs('target', v_fr, onehot=True)
  v_de_x, v_de_y = v_de_xy[:,:-1,:], v_de_xy[:,1:,:]
  res = nmt_tf.evaluate([v_en_x, v_de_x], v_de_y, batch_size=valid_size, verbose=0)
  print("Epoch {} => Loss:{}, Val Acc: {}".format(ei+1,res[0], res[1]*100.0))
```

```
Epoch 1 => Loss:4.784221172332764, Val Acc: 1.4999999664723873
Epoch 2 => Loss:4.716882228851318, Val Acc: 44.458332657814026
Epoch 3 => Loss:4.63267183303833, Val Acc: 47.333332896232605
```

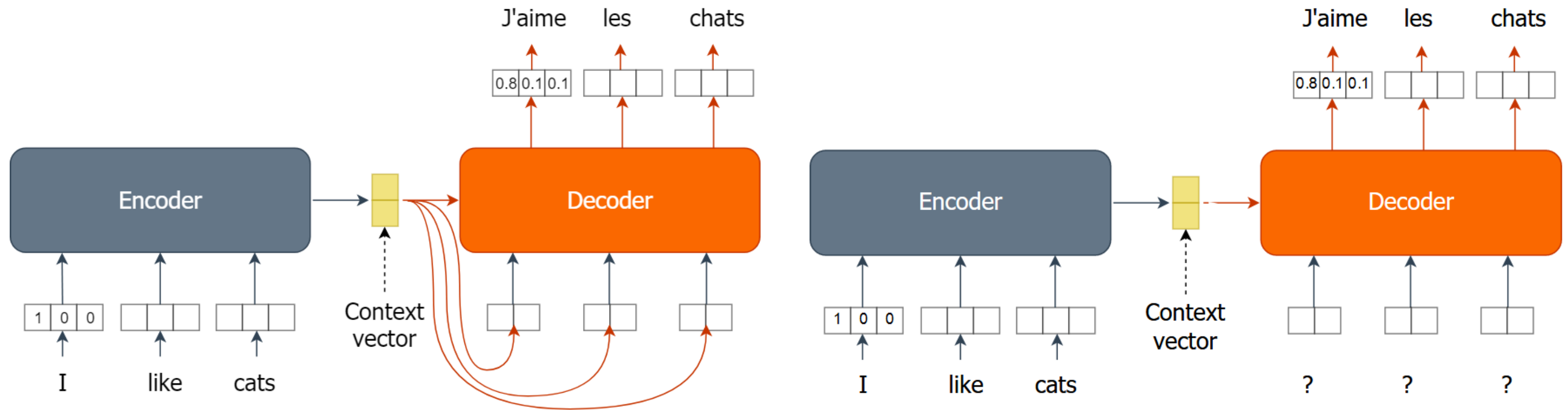# Let's train!

MACHINE TRANSLATION IN PYTHON

Generating translations from the model

MACHINE TRANSLATION IN PYTHON

Thushan Ganegedara
Data Scientist and Author

Previous model vs new model

Trained model
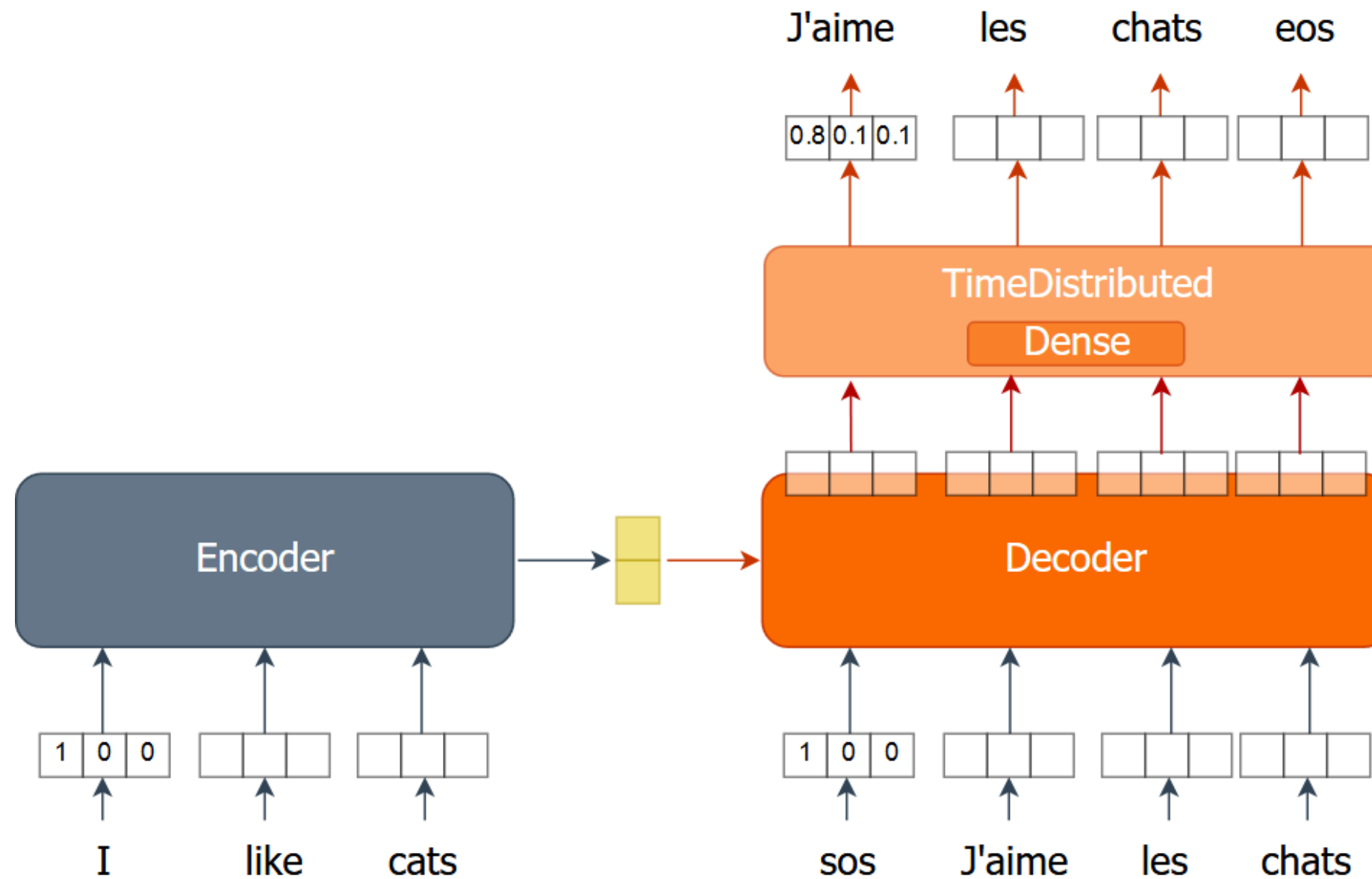
Decoder of the inference model

- Takes in
  - A onehot encoded word

  - A state input (gets the state from previous timestep)

- Produces
  - A new state

  - A prediction (i.e. a word)

- Recursively feed the predicted word and the state back to the model as inputs

Full inference model

- Inference model with the recursive decoder

- Inference model from the previous chapter

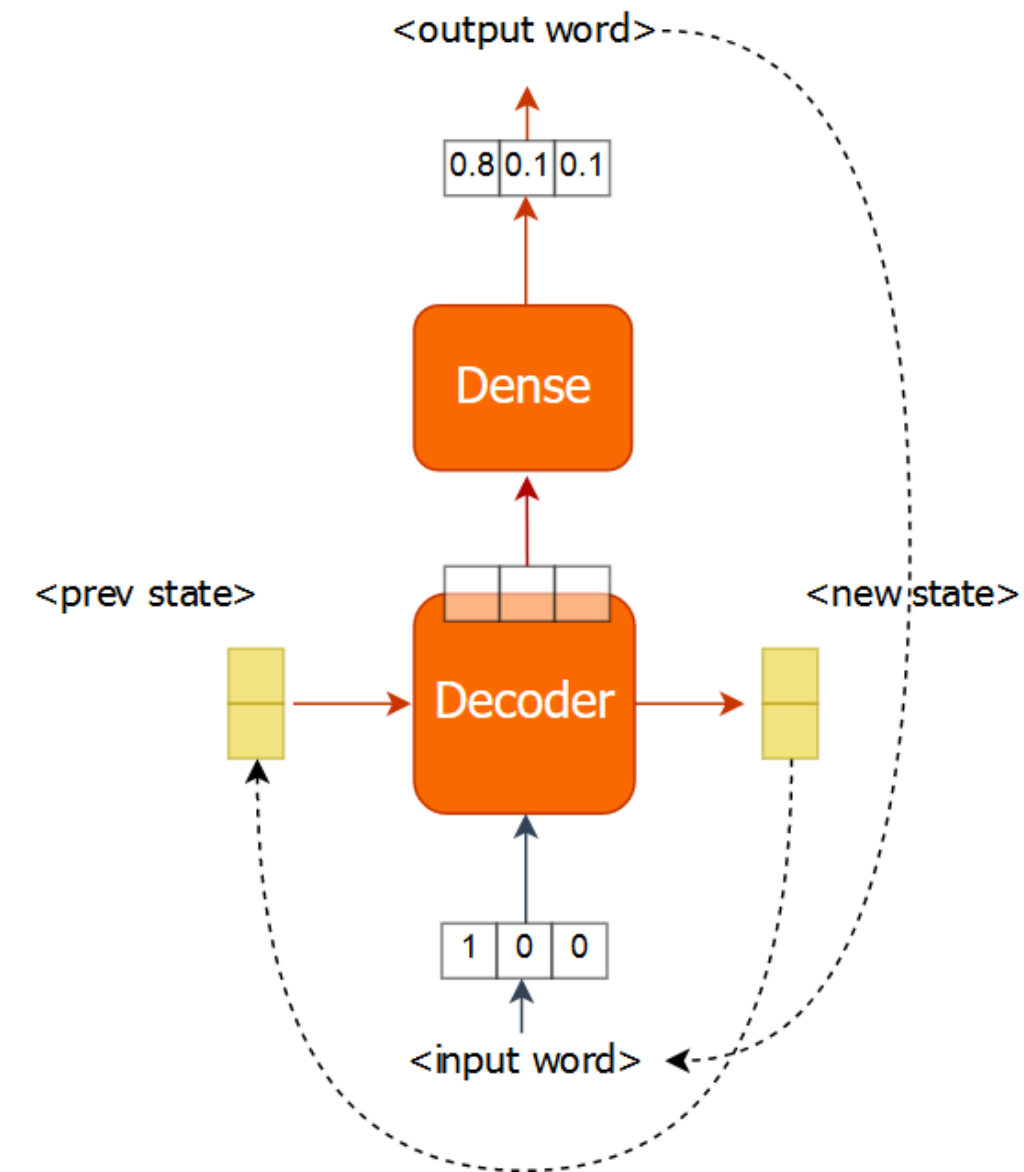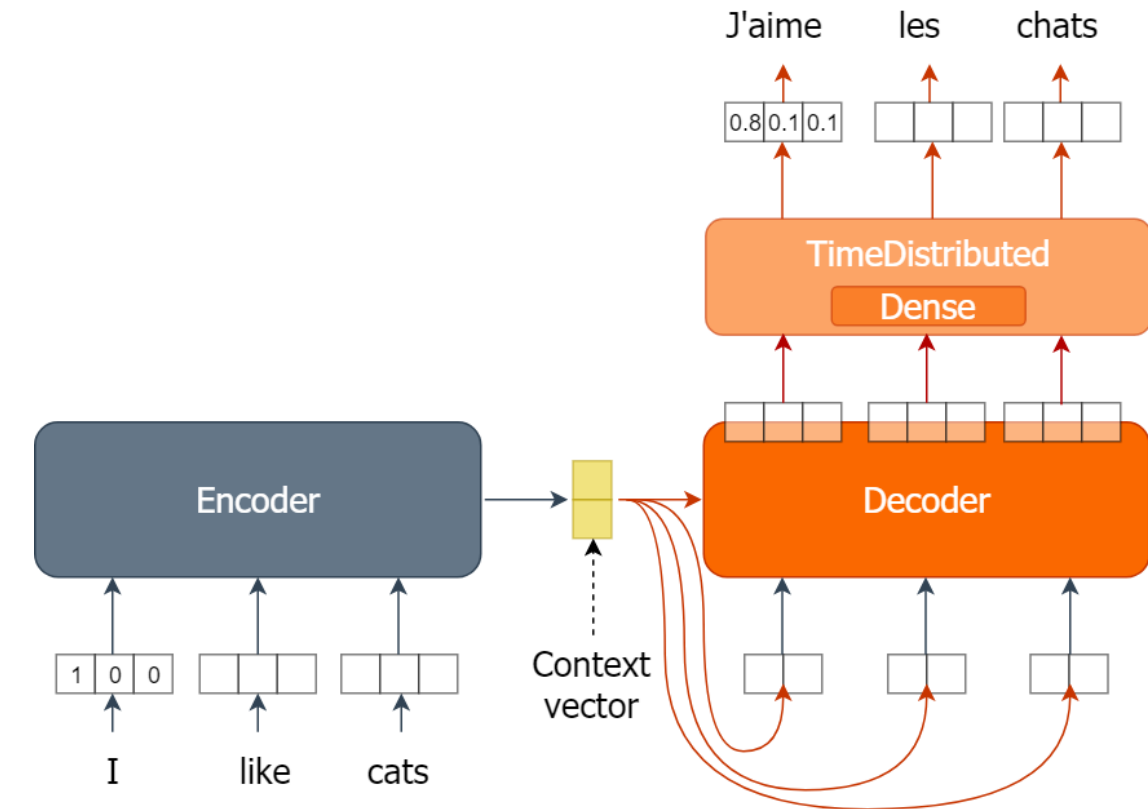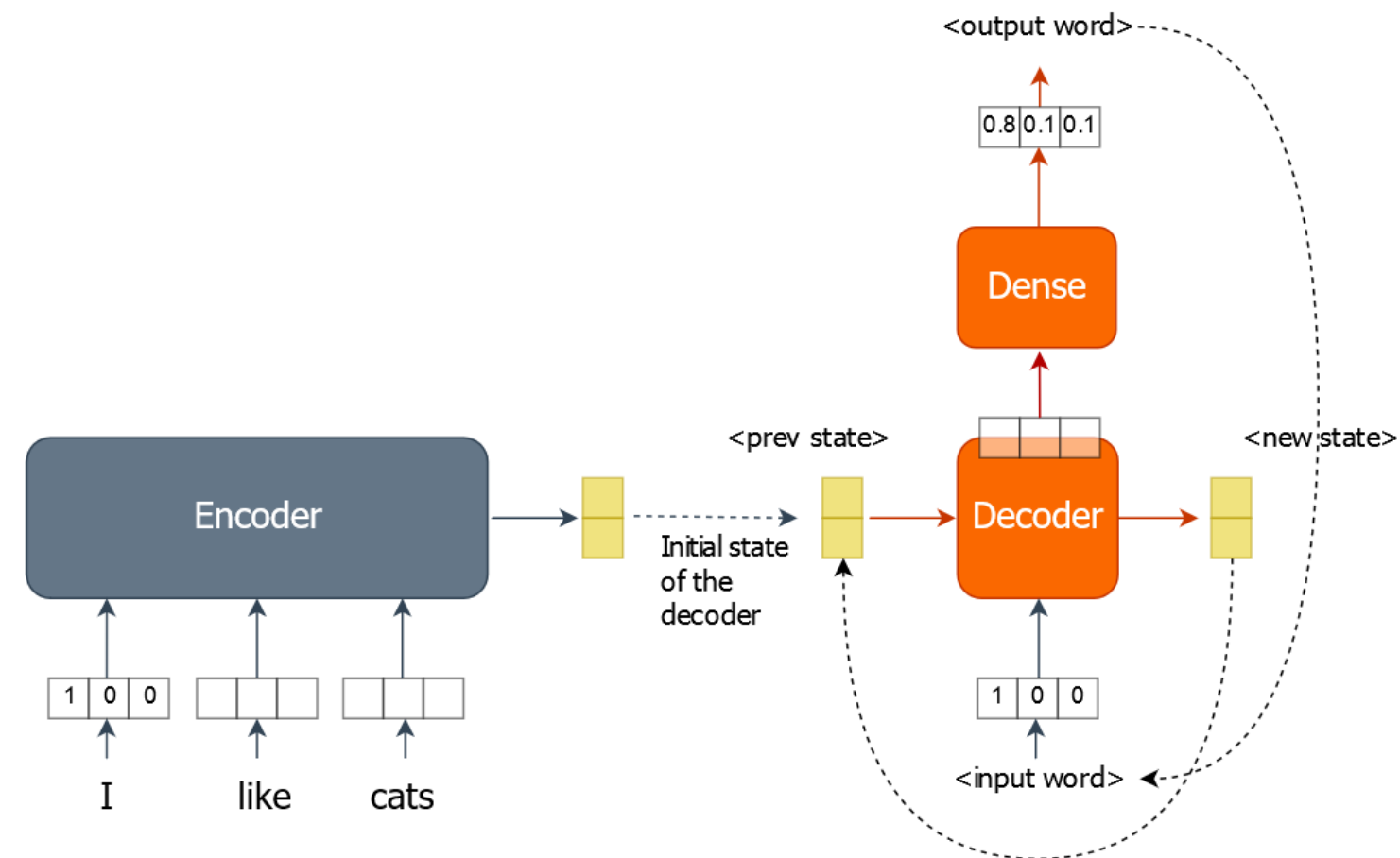# Value of sos and eos tokens

- `sos` marks beginning of a translation (i.e. a French sentence).
  - Feed in `sos` as the first word to the decoder and keep predicting

- `eos` marks the end of a translation.
  - Predictions stop when the word predicted by the model is `eos`

- As a safety measure use a maximum length the model can predict for

Defining the generator encoder

- Importing layers and Model

```python
# Import Keras layers
import tensorflow.keras.layers as layers
from tensorflow.keras.models import Model
```

- Defining model layers

```python
en_inputs = layers.Input(shape=(en_len,en_vocab))
en_gru = layers.GRU(hsize, return_state=True)
en_out, en_state = en_gru(en_inputs)
```

- Defining `Model` object

```python
encoder = Model(inputs=en_inputs, outputs=en_state)
```

Defining the generator decoder

- Defining the decoder `Input` layers

```
de_inputs = layers.Input(shape=(1, fr_vocab))
de_state_in = layers.Input(shape=(hsize,))
```

- Defining the decoder's interim `layers`

```
de_gru = layers.GRU(hsize, return_state=True)
de_out, de_state_out = de_gru(de_inputs, initial_state=de_state_in)
de_dense = layers.Dense(fr_vocab, activation='softmax')
de_pred = de_dense(de_out)
```

- Defining the decoder `Model`

```
decoder = Model(inputs=[de_inputs, de_state_in], outputs=[de_pred, de_state_out])
```

Copying the weights

- Get weights of the layer `l1`
  - `w = l1.get_weights()`

- Set the weights of the layer `l2` with `w`
  - `l2.set_weights(w)`

- In our model, there are three layers with weights
  - Encoder `GRU`, Decoder `GRU` and Decoder `Dense`

```
en_gru_w = tr_en_gru.get_weights()
en_gru.set_weights(en_gru_w)
```

Which can also be written as,

```
en_gru.set_weights(tr_en_gru.get_weights())
```

Generating translations

```
en_sent = ['the united states is sometimes chilly during
            december , but it is sometimes freezing in june .']
```

- Converting the English sentence to a sequence

```
en_seq = sents2seqs('source', en_st, onehot=True, reverse=True)
```

- Getting the context vector

```
de_s_t = encoder.predict(en_seq)
```

- Converting "sos" (initial word to the decoder) to a sequence

```
de_seq = word2onehot(fr_tok, 'sos', fr_vocab)
```
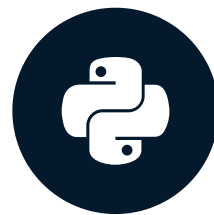
Generating translations

```python
fr_sent = ''
for _ in range(fr_len):
  de_prob, de_s_t = decoder.predict([de_seq,de_s_t])
  de_w = probs2word(de_prob, fr_tok)
  de_seq = word2onehot(fr_tok, de_w, fr_vocab)
  if de_w == 'eos': break
  fr_sent += de_w + ' '
```

Time to translate!

MACHINE TRANSLATION IN PYTHON

Using word embedding for machine translation

MACHINE TRANSLATION IN PYTHON

Thushan Ganegedara
Data Scientist and Author

Introduction to word embeddings

- One hot encoded vectors

```python
cat_vector = np.array([[1,0,0,0...,0]])
dog_vector = np.array([[0,1,0,0...,0]])
window_vector = np.array([[0,0,1,0...,0]])
```

- Word vectors

```python
cat_vector = np.array([[0.393,-0.263,0.086,0.011,-0.322,...,0.388]])
dog_vector = np.array([[0.399,-0.300,0.047,-0.059,-0.111,...,0.037]])
window_vector = np.array([[0.133,0.149,-0.307,0.090,-0.143,...,0.526]])
```

Similarity between word vectors

```python
from sklearn.metrics.pairwise import cosine_similarity
cat_vector = np.array([[0.393,-0.263,0.086,0.011,-0.322,...,0.388]])
dog_vector = np.array([[0.399,-0.300,0.047,-0.059,-0.111,...,0.037]])
window_vector = np.array([[0.133,0.149,-0.307,0.090,-0.143,...,0.526]])
```

```python
cosine_similarity(cat_vector, dog_vector)
```

```
0.601
```

```python
cosine_similarity(cat_vector, window_vector)
```
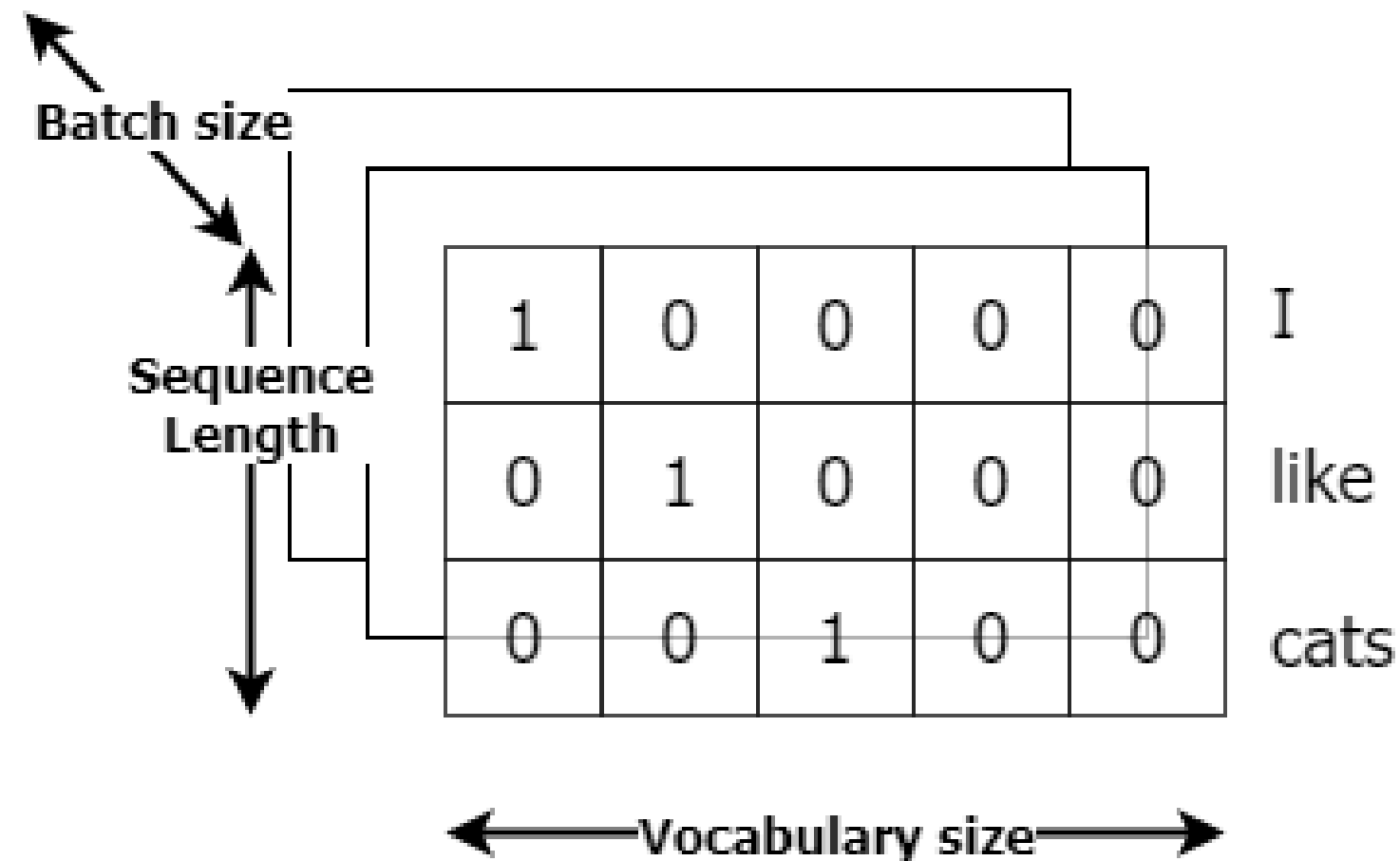
```
0.323
```

[1] https://nlp.stanford.edu/projects/glove/

Implementing embeddings for the encoder

- Without an embedding layer

```
en_inputs = Input(shape=(en_len, en_vocab))
```
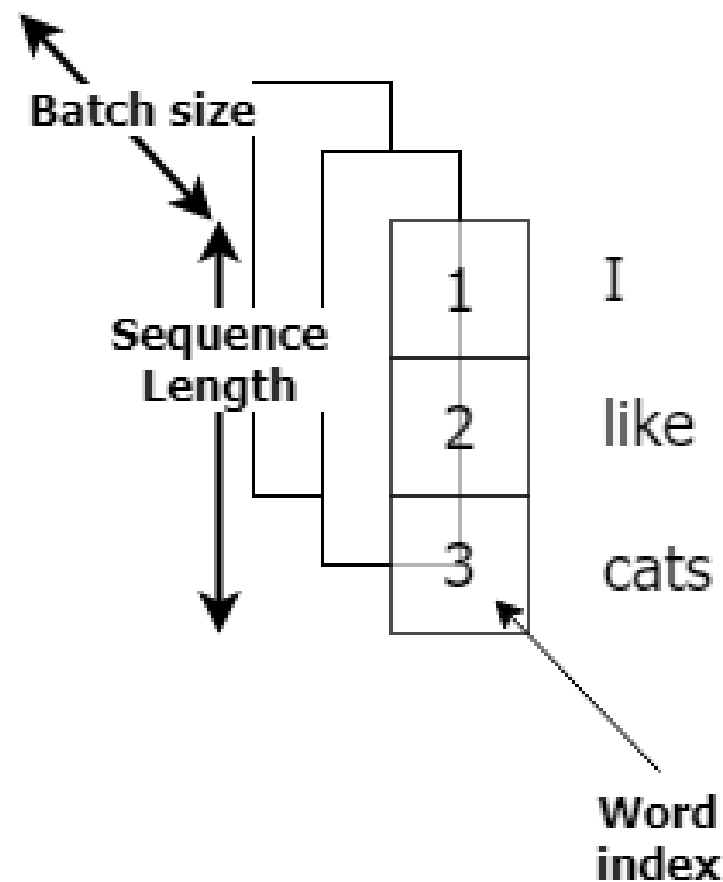
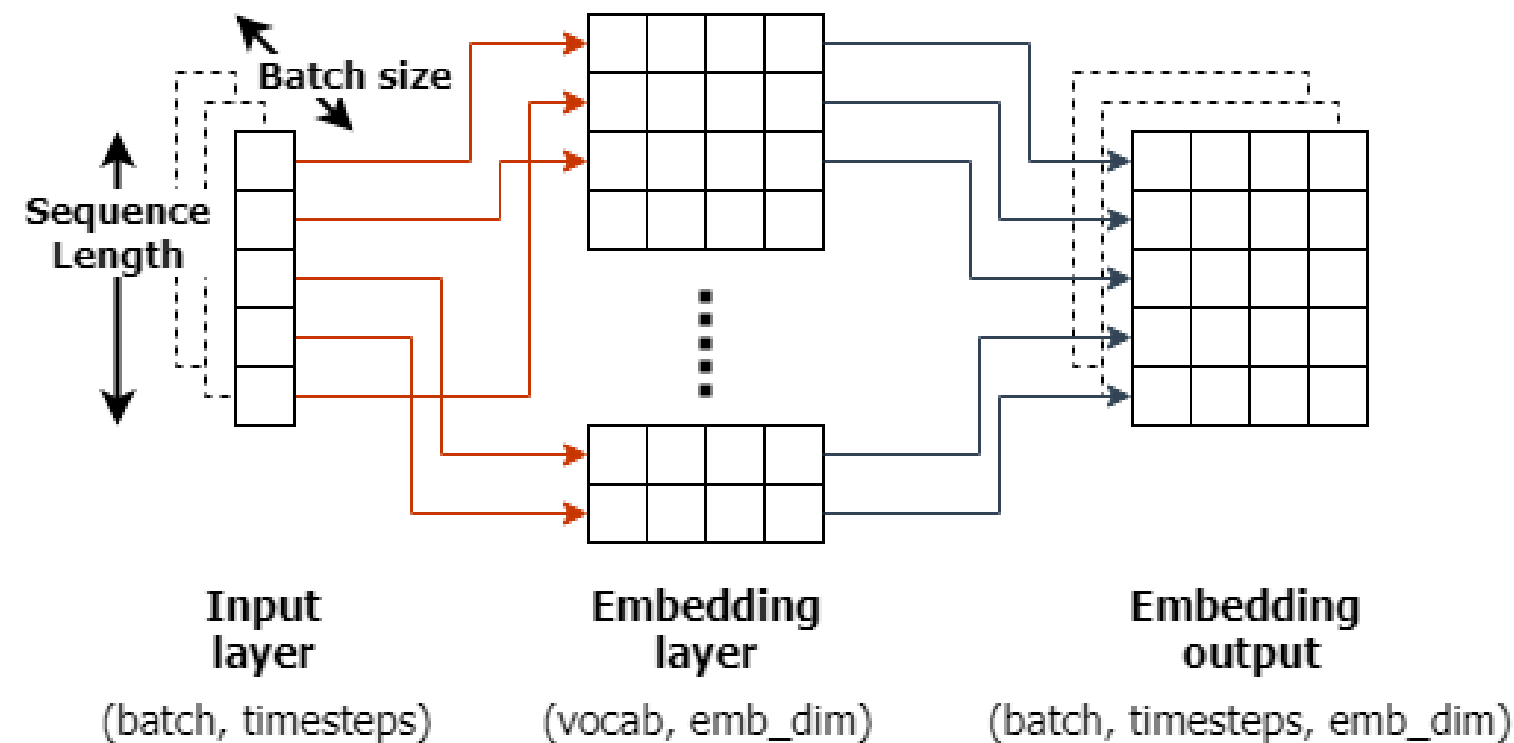# Implementing embeddings for the encoder

- With an embedding layer

```
en_inputs = Input(shape=(en_len,))
```

Implementing embeddings for the encoder

```
en_inputs = Input(shape=(en_len,))
en_emb = Embedding(en_vocab, 96, input_length=en_len)(en_inputs)
```


Input layer

(batch, timesteps)

Embedding layer

(vocab, emb_dim)

Embedding output

(batch, timesteps, emb_dim)

Implementing the encoder with embedding

```
en_inputs = Input(shape=(en_len,))
en_emb = Embedding(en_vocab, 96, input_length=en_len)(en_inputs)
en_out, en_state = GRU(hsize, return_state=True)(en_emb)
```
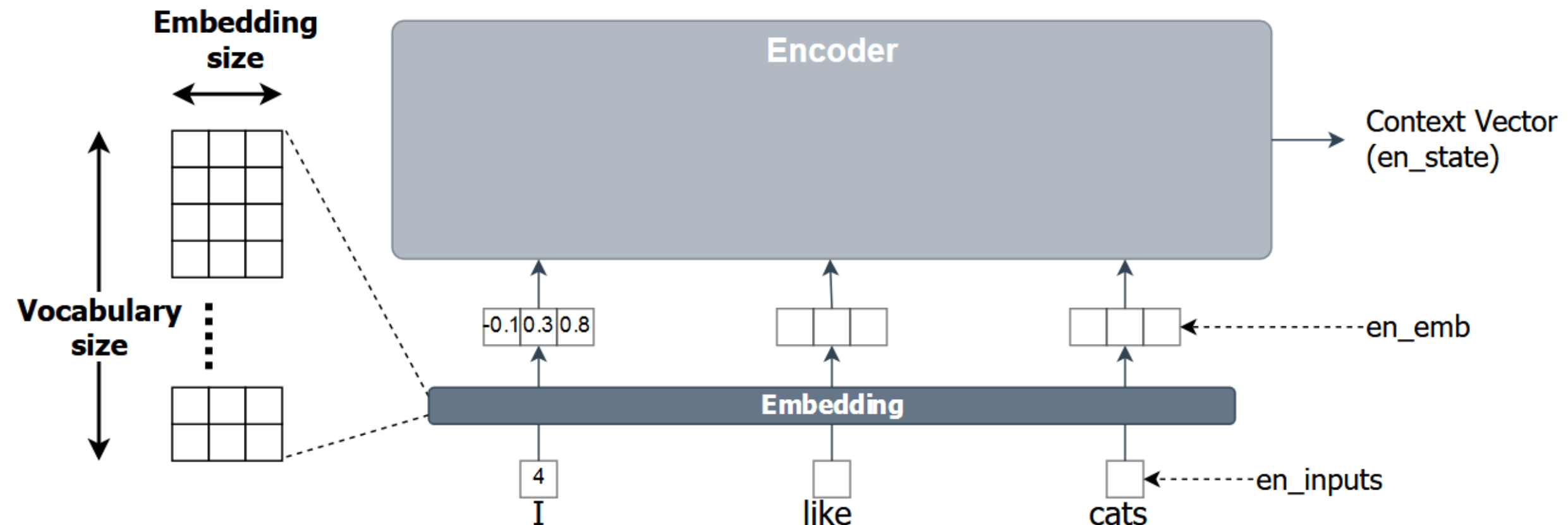
Implementing the decoder with embedding

```
de_inputs = Input(shape=(fr_len-1,))
de_emb = Embedding(fr_vocab, 96, input_length=fr_len-1)(de_inputs)
de_out, _ = GRU(hsize, return_sequences=True, return_state=True(
    de_emb, initial_state=en_state)
```
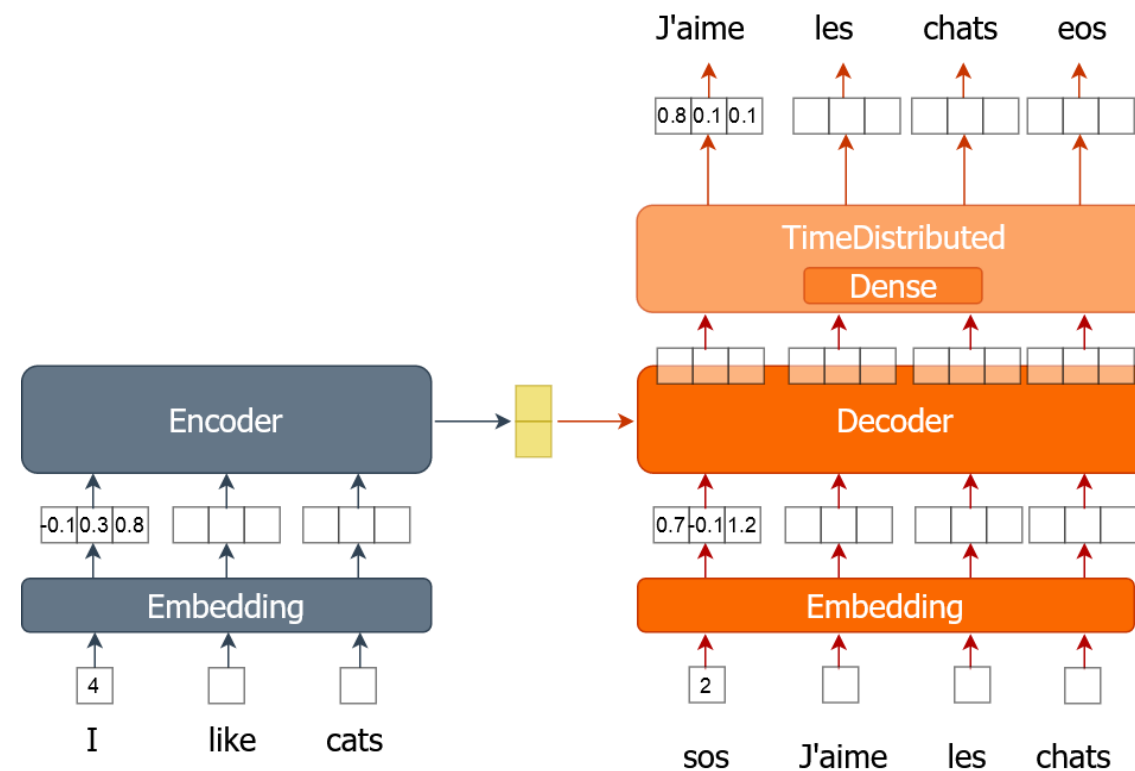
Training the model

```python
for ei in range(3):
  for i in range(0, train_size, bsize):
    en_x = sents2seqs('source', tr_en[i:i+bsize], onehot=False, reverse=True)
    de_xy = sents2seqs('target', tr_fr[i:i+bsize], onehot=False)
    de_x = de_xy[:,:-1]
    de_xy_oh = sents2seqs('target', tr_fr[i:i+bsize], onehot=True)
    de_y = de_xy_oh[:,1:,:]
    nmt_emb.train_on_batch([en_x, de_x], de_y)
    res = nmt_emb.evaluate([en_x, de_x], de_y, batch_size=bsize, verbose=0)
    print("{} => Loss:{}, Train Acc: {}".format(ei+1,res[0], res[1]*100.0))
```

Let's practice!

MACHINE TRANSLATION IN PYTHON

Wrap-up and the final showdown

MACHINE TRANSLATION IN PYTHON
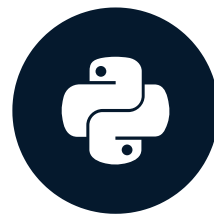
Thushan Ganegedara
Data Scientist and Author

What you've done so far

- Chapter 1
  - Introduction to encoder-decoder architecture

  - Understanding GRU layer

- Chapter 2
  - Implementing the encoder

  - Implementing the decoder

 - Implementing the decoder prediction layer

What you've done so far

- Chapter 3
  - Preprocessing data

  - Training the machine translation model

  - Generating translations

- Chapter 4
  - Introduction to teacher forcing

  - Training a model with teacher forcing

  - Generating translations

  - Using word embeddings for machine translation

Machine transation models

- Model 1
  - The encoder consumes English words (onehot encoded) and outputs a context vector
  - The decoder consumes the context vector and outputs the translation

- Model 2
  - The encoder consumes English words (onehot encoded) and outputs a context vector
  - The decoder consumes a given word (onehot encoded) of the translation and predicts the next word

- Model 3
  - Instead of onehot encoding, uses word vectors
  - Word vectors capture the semantic relationship between words

Performance of different models

Validation accuracy of different NMT models
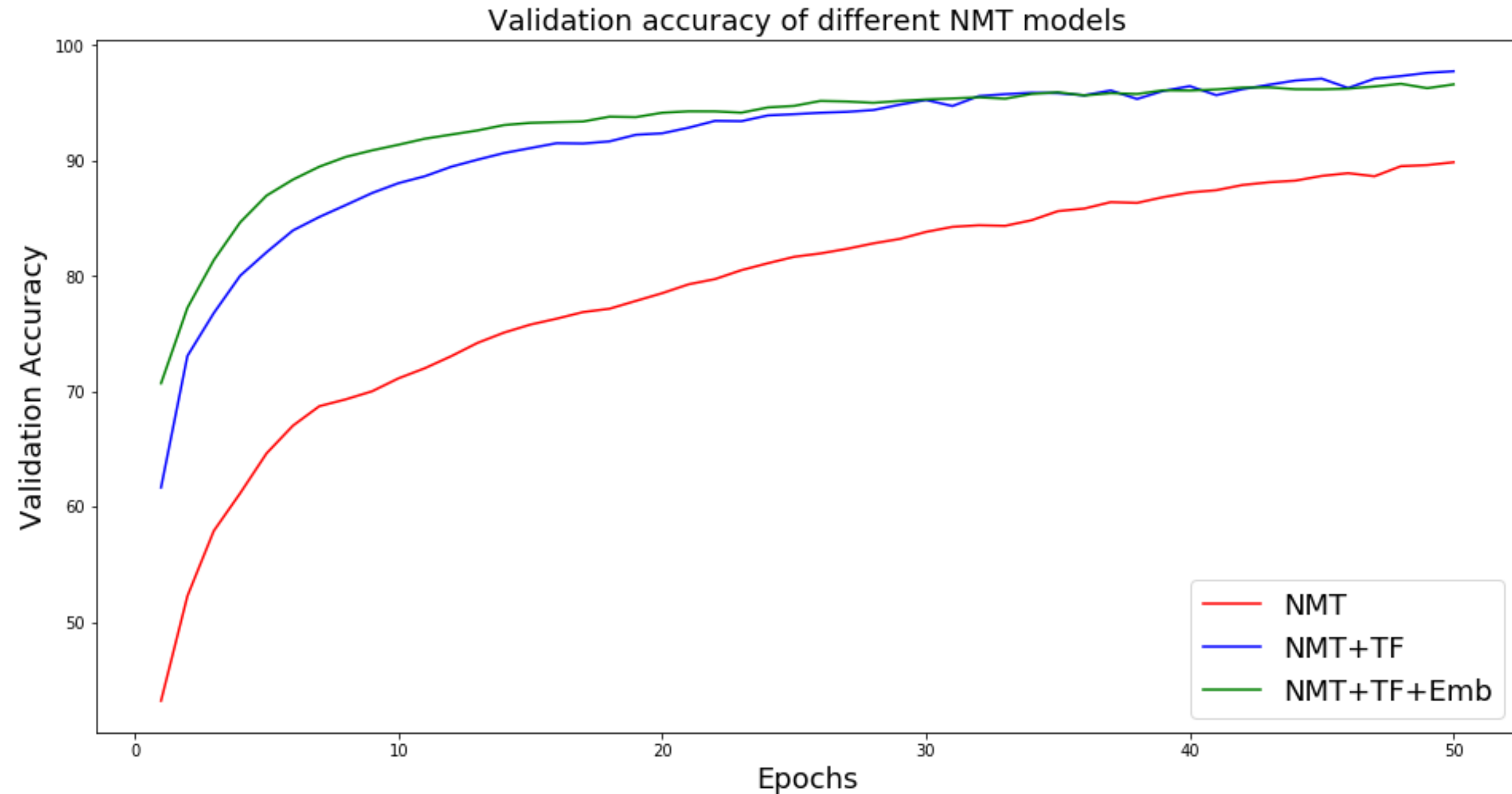
Latest developments and further reading

- Evaluating machine translation models
  - BLEU score (**Papineni et al., BLEU: a Method for Automatic Evaluation of Machine Translation.**)

- Word piece models
  - Enables the model to avoid out of vocabulary words (**Sennrich et al., Neural Machine Translation of Rare Words with Subword Units.**)

- Transformer models (**Vaswani et al., Attention Is All You Need**)
  - State-of-the-art performance on many NLP tasks including machine translation
  - Has an encoder-decoder architecture, but does not use sequential models
  - The latest Google machine translator is a Transformer model

All the best!

MACHINE TRANSLATION IN PYTHON