Georgia Tech

Neural Machine Translation with Attention

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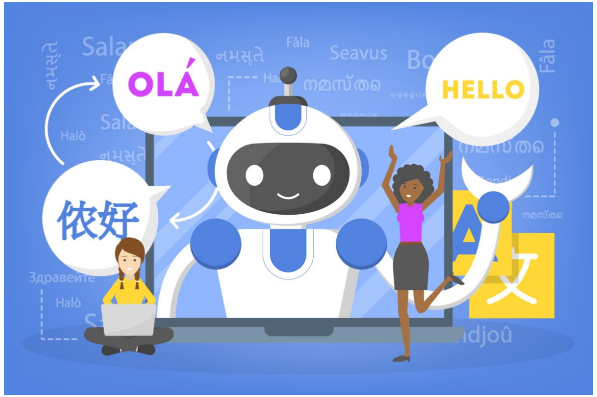
Background

Types of Machine Translation:

- Rule-Based Machine Translation (RBMT): Use a bilingual dictionary to map words
- Statistical Machine Translation (SMT): Use Bayes Rule to learn model based on parallel corpus
- Neural Machine Translation (NMT): Use a single neural network to translate

Motivation:

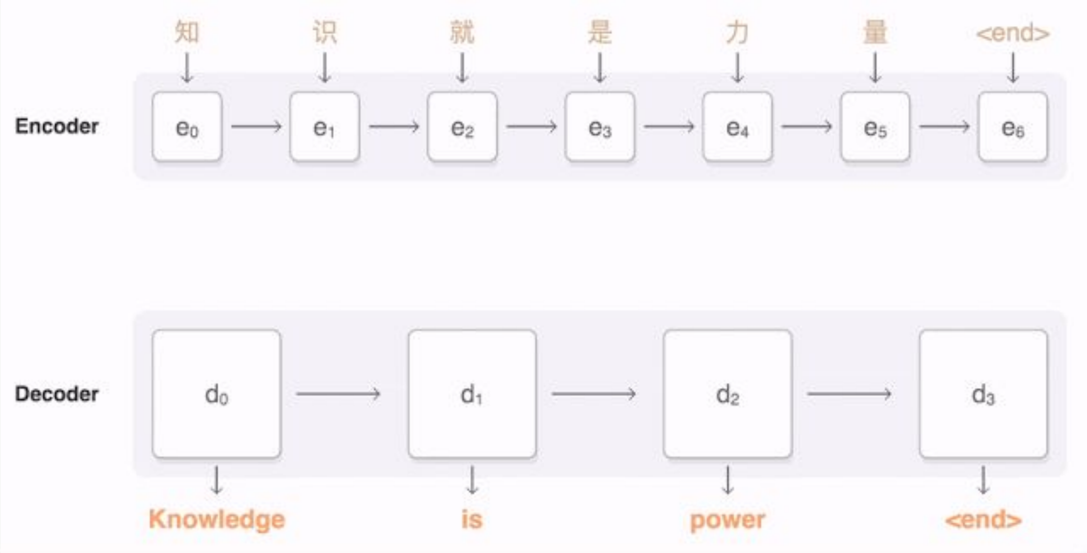
- We learned SMT in class and used RBMT in hw6
- Google Translator is based on SMT and NMT.
- Deep learning techniques like seq2seq model and attention mechanism are successful in NMT.



NMT Overview

Encoder-Decoder architecture

- Encoder: reads the source sentence build a "thought" vector
- Decoder: processes the sentence vector to emit a translation



Data Introduction

122936 Spanish to English sentence pairs from Tatoeba Corpus

Format: English + TAB + Spanish + TAB + Attribution

Examples:

I've seen them.	Los vi.	CC-BY 2.0 (France) Attribution: tatoeba.org #2248417 (CK)...
If only I knew!	¡Ojalá lo supiera!	CC-BY 2.0 (France) Attribution: tatoeba.org #276985 (CM)...
Is Tom at home?	¿Está Tom en casa?	CC-BY 2.0 (France) Attribution: tatoeba.org #2262070 (CK)...

Feature Construction

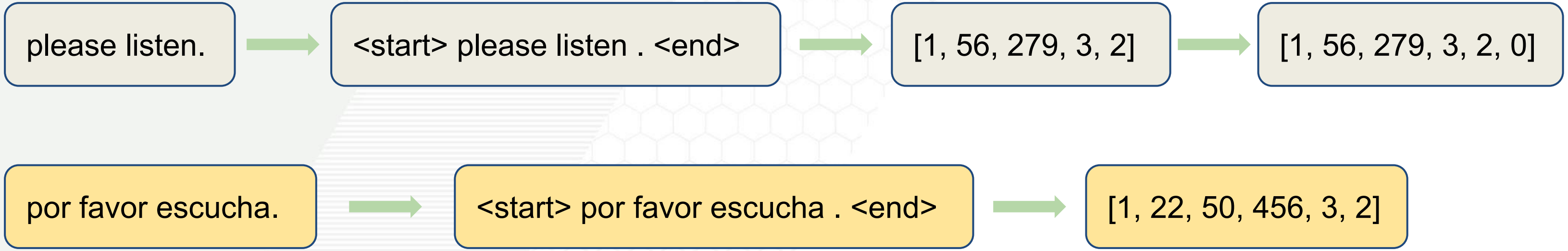
Prepare the data:

1. Add a start and end token to each sentence.

2. Remove special characters.

3. Create a word index and reverse word index

4. Pad each sentence to a maximum length.



please listen. → <start> please listen . <end> → [1, 56, 279, 3, 2] → [1, 56, 279, 3, 2, 0]

por favor escucha. → <start> por favor escucha . <end> → [1, 22, 50, 456, 3, 2]

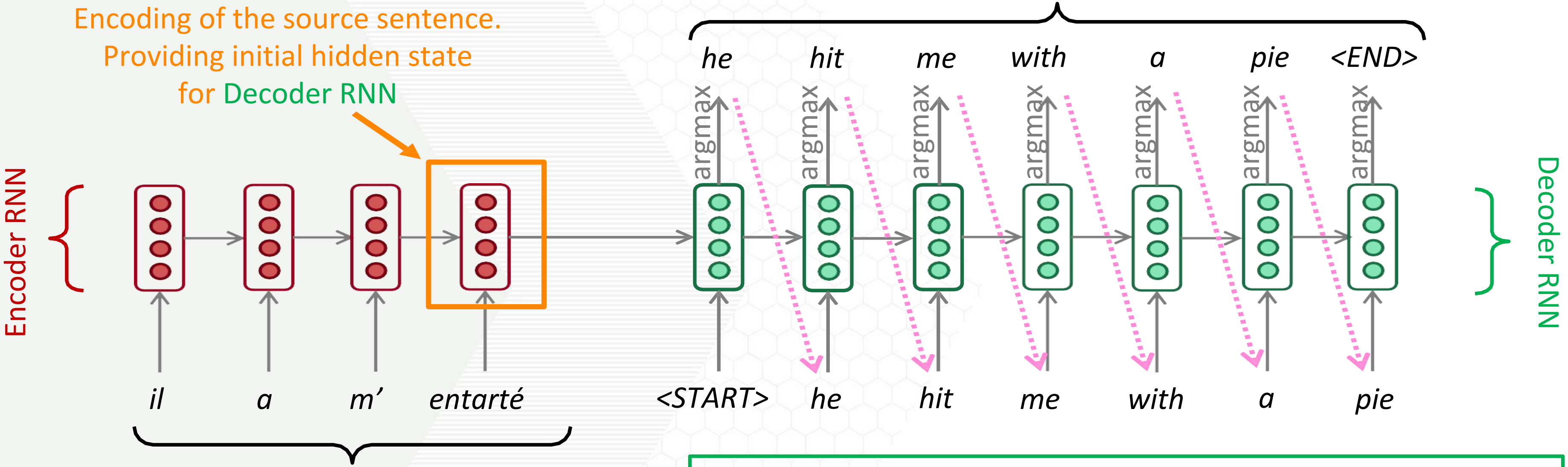
Encoder and Decoder Model

The sequence-to-sequence model

Encoding of the source sentence.

Providing initial hidden state

for Decoder RNN



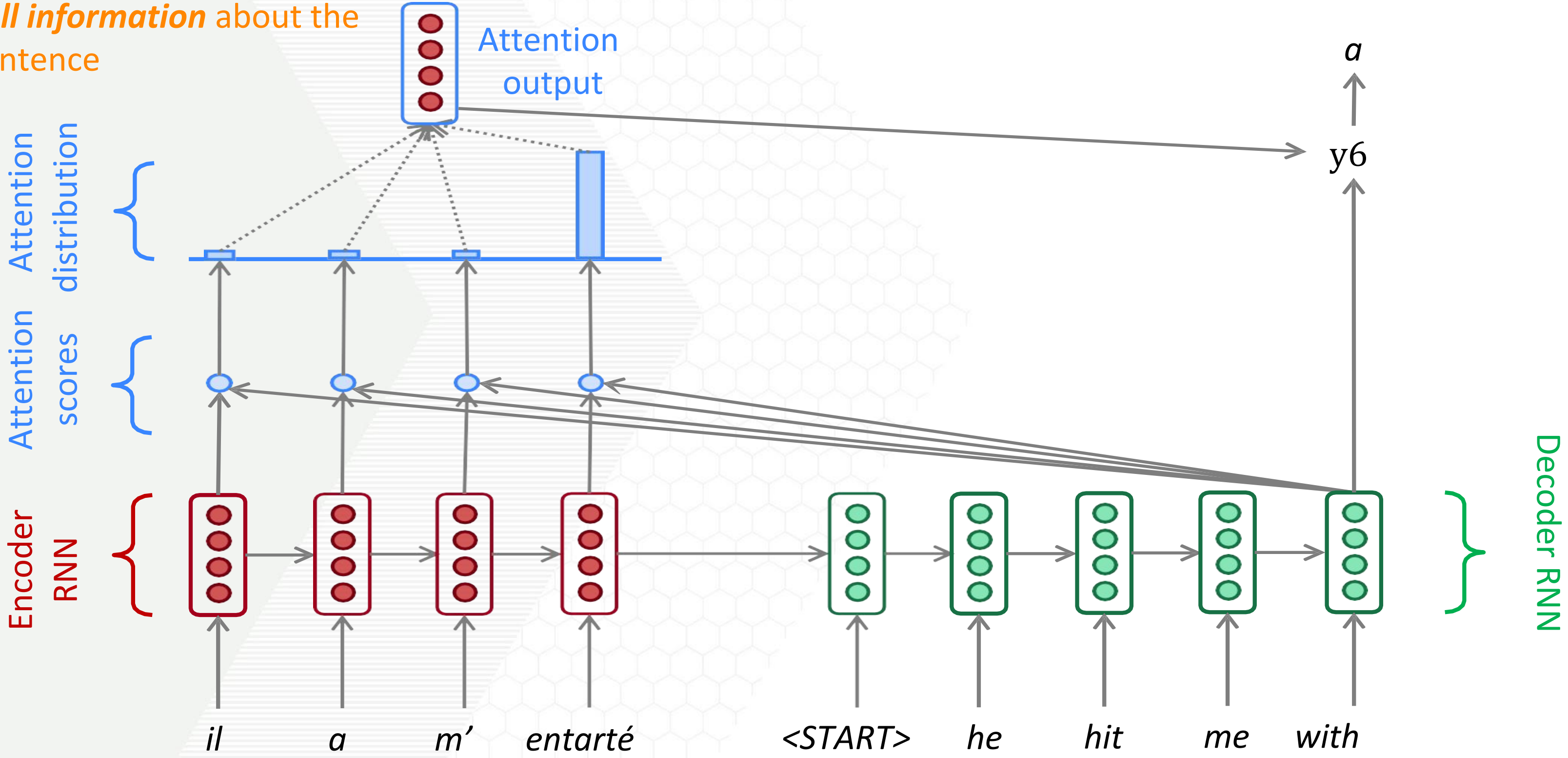
Encoder RNN produces an encoding of the source sentence.

Decoder RNN is a Language Model that generates target sentence, *conditioned on* encoding.

Note: This diagram shows **test time** behavior: decoder output is fed in ------> as next step’s input

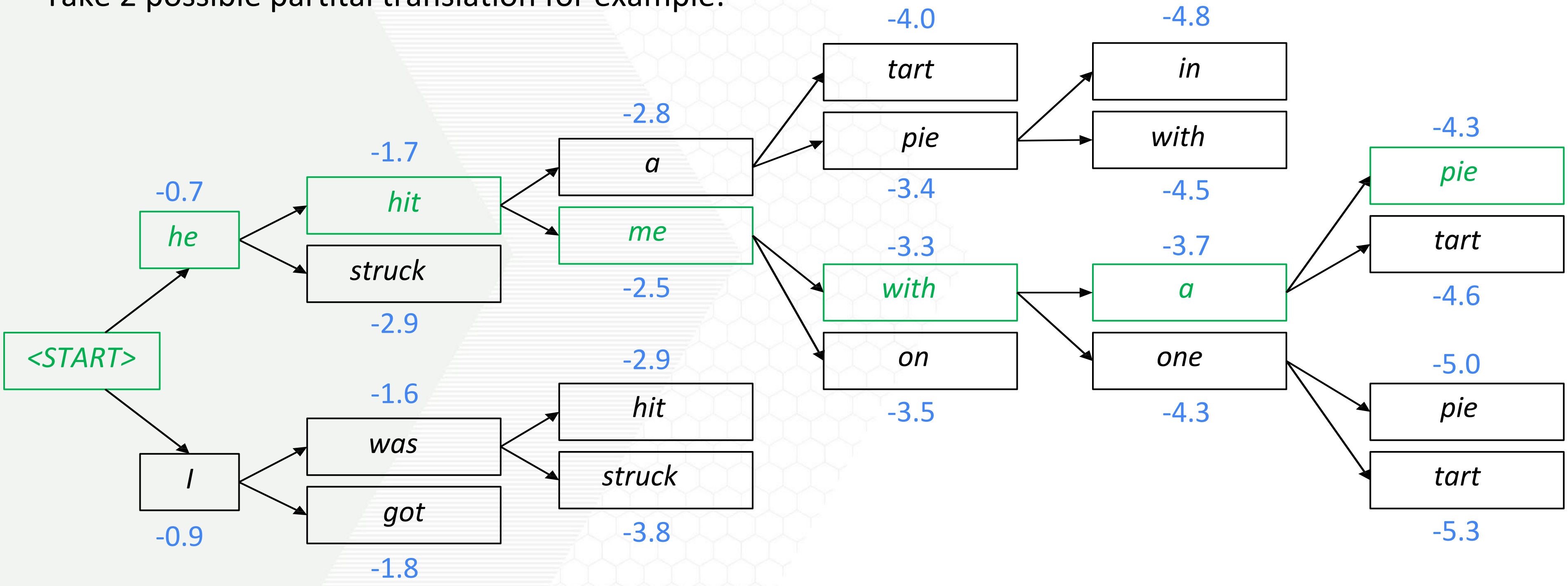
Attention Improvement

Encoding of the source sentence capture ***all information*** about the source sentence



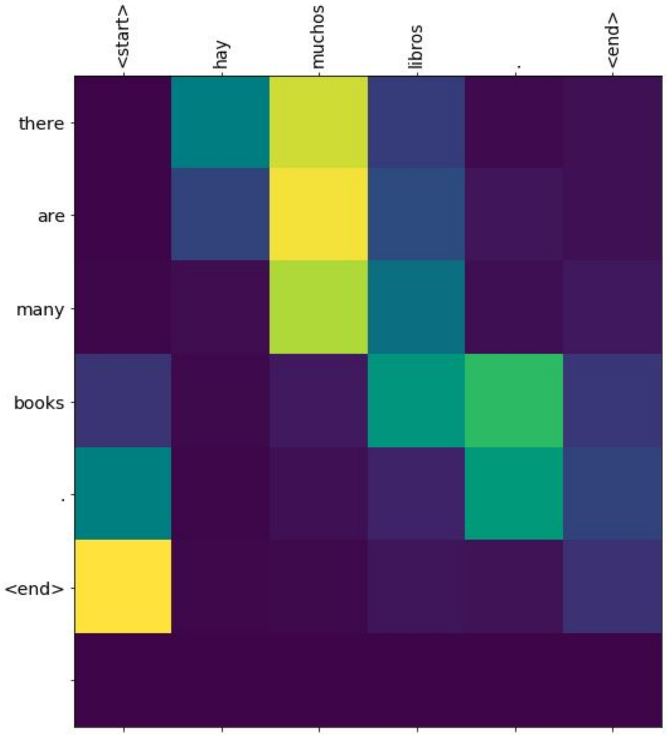
Translation Process

Take 2 possible partital translation for example:



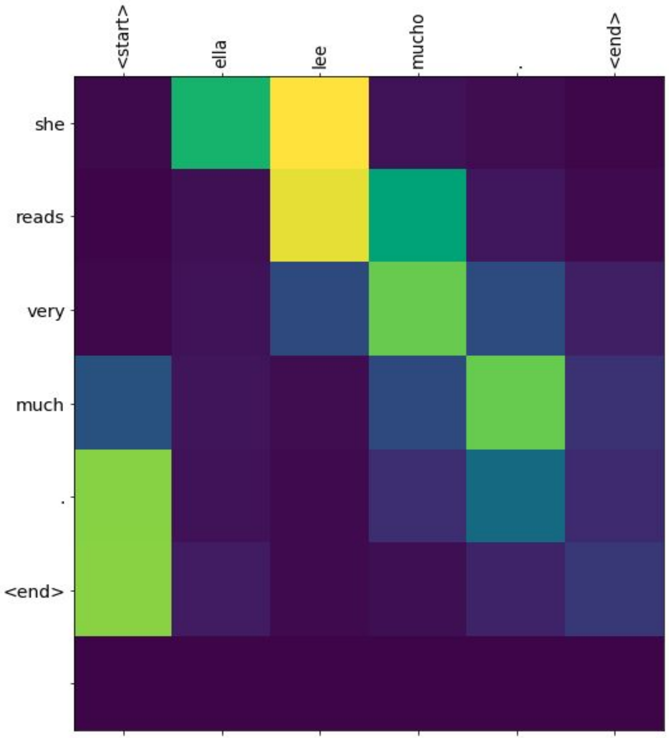
Good Cases

```
Input: <start> hay muchos libros . <end>
Predicted translation: there are many books . <end>
```



```
Gold: There are many books.
```

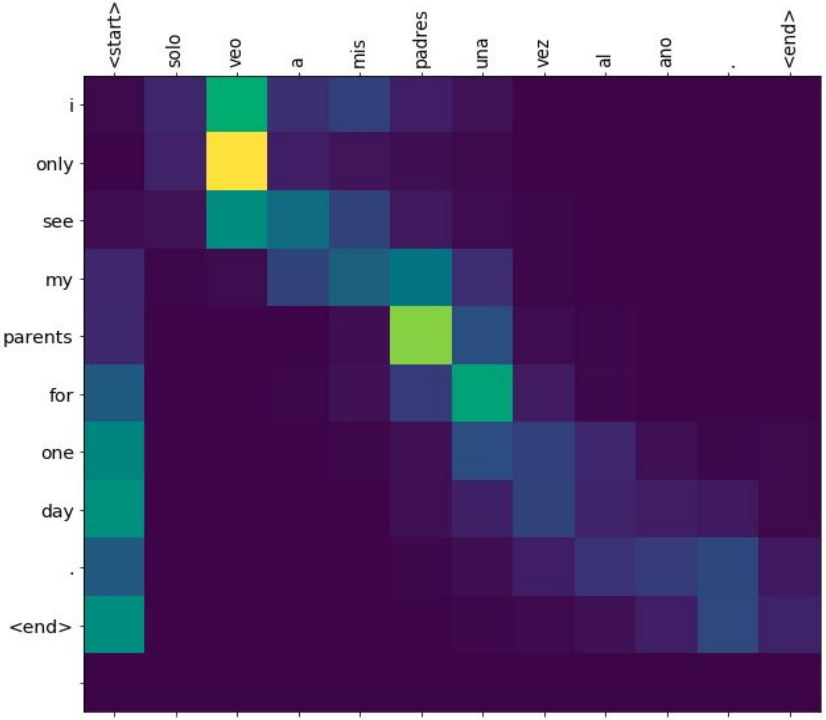
```
Input: <start> ella lee mucho . <end>
Predicted translation: she reads very much . <end>
```



```
Gold: She reads a lot
```

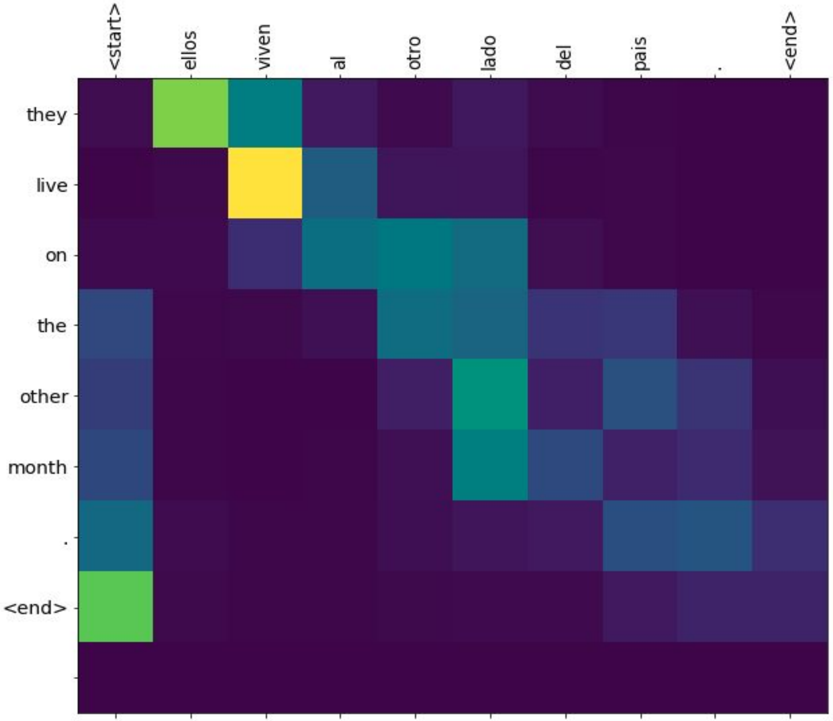
Bad Cases

```
Input: <start> solo veo a mis padres una vez al ano . <end>
Predicted translation: i only see my parents for one day . <end>
```



```
Gold: I only see my parents once a year.
```

```
Input: <start> ellos viven al otro lado del pais . <end>
Predicted translation: they live on the other month . <end>
```



```
Gold: They live on the other side of the country.
```

NMT Discussion

Advantages of NMT:

- Better performance, more fluent
- A single neural network to be optimized end-to-end and easy to train
- Requires much less human engineering effort. ***No rules! No dictionaries!***
- One method for ***all languages!***

Disadvantages of NMT:

- Hard to debug
- Difficult to control
- Depends on the data quality and model parameters
- Picks up the **bias** in data, like gender discrimination and so on

My Thoughts

- For the future work, I can train my model with larger dataset and more epochs to improve the performance.
- Google provides detailed tutorial and it's not so difficult to build your own neural machine translation tool on any pair of languages.
- Deep learning really reduce much more human work in machine translation than traditional methods. Neural machine translation is the **TRUE** machine translation.

References

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