TRANSLATION WITH A SEQUENCE TO SEQUENCE NETWORK AND ATTENTION

- Translate from French to English

- Sequence to sequence network
  : two RNN work together to transform one sequence to another.
  - Encoder : condences an input sequence into a vector
  - Decoder : unfolds the vector into a new sequence

Requirements

```
from __future__ import unicode_literals, print_function, division
from io import open
import unicodedata
import string
import re
import random

import torch
from torch.nn import nn
from torch import optim
import torch.nn.functional as F

device = torch.device ("cuda" if torch.cuda.is_available() else "cpu")
```

Loading data files

- English to French pairs
- unique index per word & one-hot vector

SOS	EOS	the	a	is	and	or	
01	02	03	04	05	06	07	..

and = < 0 0 0 0 0 1 0 ... >

- class Lang : helper class
  - word → index (word2index)
  - index → word (index2word)
  - Count of each word (word2count)

```python
SOS_token = 0
EOS_token = 1

class Lang:
    def __init__(self, name):
        self.name = name
        self.word2index = {}
        self.word2count = {}
        self.index2word = {0: "SOS", 1: "EOS"}
        self.n_words = 2    # Count SOS and EOS

    def addSentence(self, sentence):
        for word in sentence.split(' '):
            self.addWord(word)

    def addWord(self, word):
        if word not in self.word2index:
            self.word2index[word] = self.n_words
            self.word2count[word] = 1
            self.index2word[self.n_words] = word
            self.n_words += 1
        else:
            self.word2count[word] += 1
```

To simplify:

- turn Unicode characters to ASCII
- make everything lowercase
- trim most punctuation

```python
def unicodeToAscii(s):
    return ''.join(
        c for c in unicodedata.normalize('NFD', s)
        if unicodedata.category(c) != 'Mn'
    )


# Lowercase, trim, and remove non-letter characters
def normalizeString(s):
    s = unicodeToAscii(s.lower().strip())
    s = re.sub(r"([.!?])", r" \1", s)
    s = re.sub(r"[^a-zA-Z.!?]+", r" ", s)
    return s
```

To read the data file :

- split the file into lines

↓

- split lines into pairs

To translate from other language → English : reverse flag

```
def readLangs (lang1, lang2, reverse = False) :
    print ("Reading lines ...")

    # Read the file and split into lines
    lines = open ('data/%s-%s.txt' % (lang1, lang2), encoding ='utf-8'). \
        read(). strip(). split('\n')

    # split every line into pairs and normalize
    pairs = [[ normalizeString (s) for s in l.split ('\t')] for l in lines]

    # Reverse pairs, make Lang instances
    if reverse :
        pairs = [ list (reversed (p)) for p in pairs ]
        input_lang = Lang ( lang2)
        output_lang = Lang (lang1 )
    else :
        input_lang = Lang ( lang 1)
        output_lang = Lang (lang 2)
    return input_lang, output_lang, pairs
```

To train quickly :

- trim the dataset to only relatively short & simple sentences.
- maximum length : 10 words (includes ending punctuation)
- filtering to sentences that translate to the form " I am " or "He is" etc.

```
MAX_LENGTH = 10

eng_prefixes = (
    "i am ", " i am", " he is", "he s",
    " she is", "she s", "you are", "you re",
    "we are", "we re", "they are", "they re"
)

def filterPair(p):
    return  len(p[0].split(' ')) < MAX_LENGTH and \
        len(p[1].split(' ')) < MAX_LENGH and \
        p[1]. startswith (eng_prefixes)

def filterPairs(pairs):
    return [pair for pair in pairs if filterPair(pair)]
```

Full process for preparing the data is :

- Read text file and split into lines, split lines into pairs
- Normalize text, filter by length & content
- Make word lists from sentences in pairs

```
def prepareData (lang1, lang2, reverse = False) :
    input_lang, output_lang, pairs = readLangs ( lang1, lang2, reverse )
    print ("Read %s sentence pairs" % len(pairs))
    pairs = filterPairs (pairs)
    print ("Trimmed to %s sentence pairs" % len (pairs))
    print ("Counting words ...")
    for pair in pairs :
        input_lang. addSentence (pair[0])
        output_lang. addSentence (pair[1])
    print ("Counted words : ")
    print ( input_lang. name , input_lang . n_words )
    print ( output_lang. name, output_lang. n_words )
    return input_lang, output_lang , pairs

input_lang, output_lang, pairs = prepareData ('eng', 'fra', True)
print (random. choice (pairs))
```

The Seq2Seq Model

- RNN (Recurrent Neural Network)

  : a network that operates on a sequence and uses its own output as input for subsequent steps.

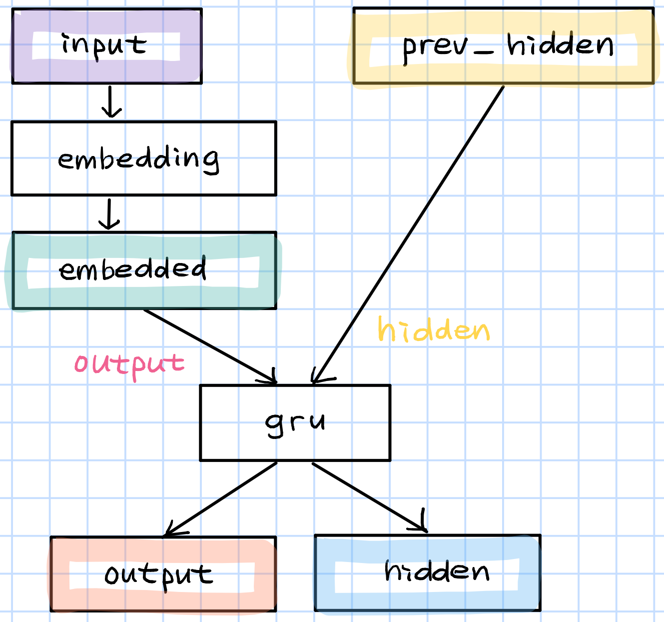
  - Encoder : reads an input sequence

    ↓ outputs a single vector

  - Decoder : reads the vector to produce an output sequence

The Encoder

- RNN that outputs some value for every word from the input sentence.
- For every input word the encoder outputs a vector and a hidden state
- uses the hidden state for the next input words



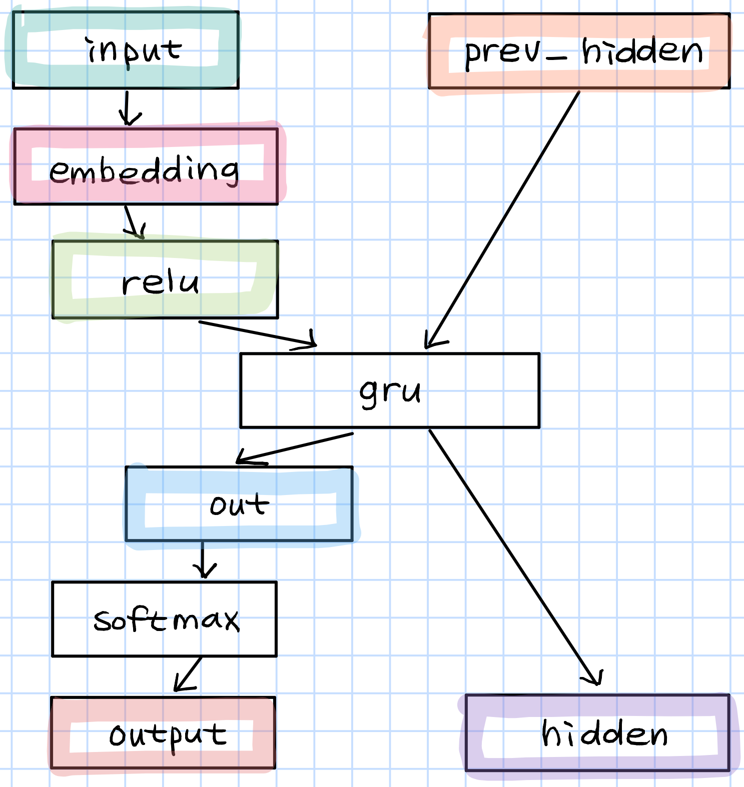

```
class EncoderRNN (nn.Module) :
    def __init__ (self, input_size, hidden_size) :
        super (EncoderRNN , self). __init__()
        self. hidden_size = hidden_size

        self. embedding = nn. Embedding (input_size, hidden_size)
        self. gru = nn. GRU ( hidden_size, hidden_size )

    def forward (self, input, hidden) :
        embedded = self. embedding (input). view ( 1, 1, -1)
        output = embedded
        output, hidden = self. gru (output, hidden)
        return output, hidden

    def initHidden (self) :
        return torch. zeros ( 1, 1, self. hidden_size , device = device)
```

The Decoder

: another RNN that takes the encoder output vector(s)
and outputs a sequence of words to create the translation

Simple Decoder

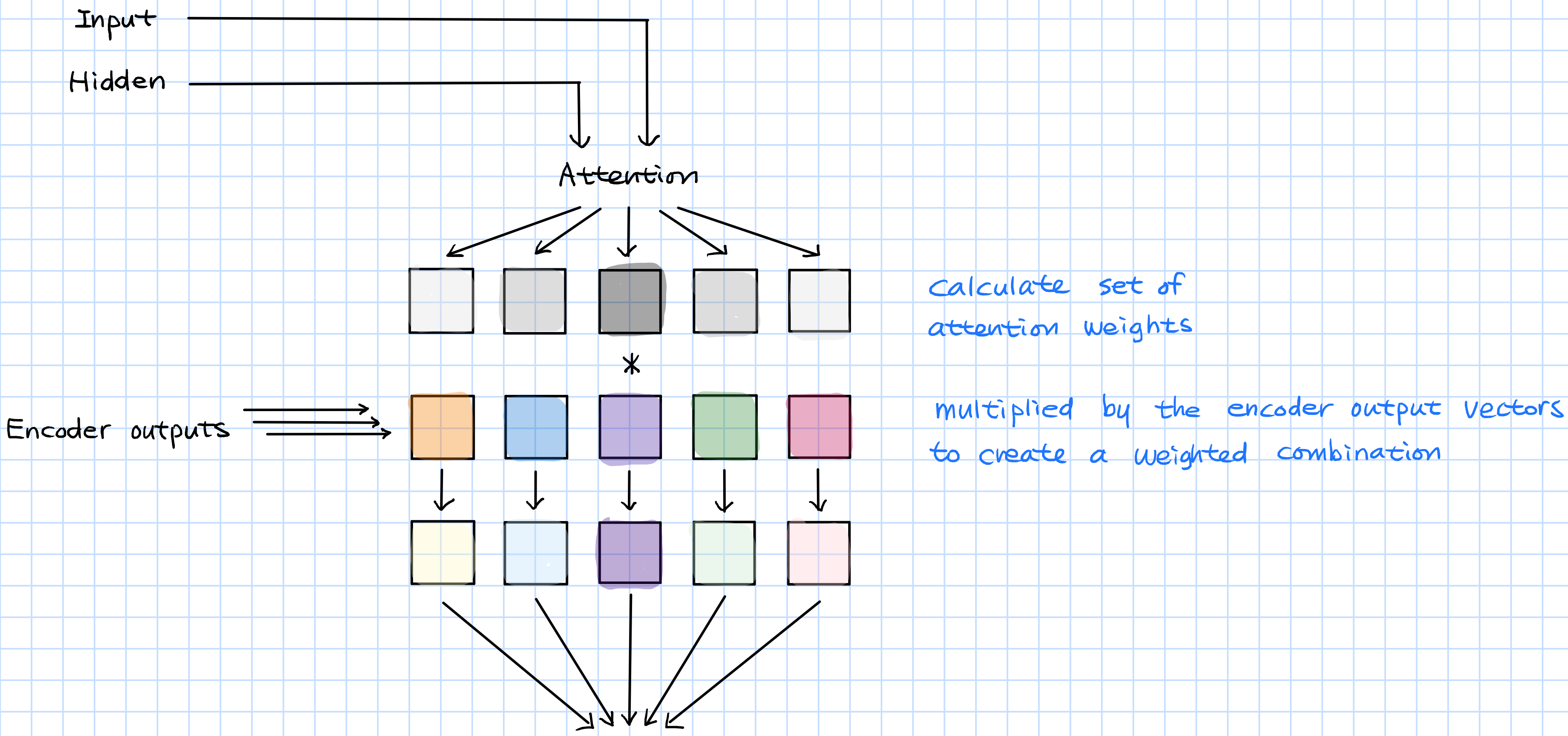
- use only last output of the encoder.
  sometimes called "context vector"
- Context vector is used as the initial hidden state of the decoder.
- At every step of decoding, the decoder is given an input token & hidden state.
  - initial input token : start - of - string <SOS>
  - first hidden state : context vector (the encoder's last hidden state)




```
class DecoderRNN (nn.Module):
    def __init__(self, hidden_size, output_size):
        super(DecoderRNN, self).__init__()
        self.hidden_size = hidden_size

        self.embedding = nn.Embedding(output_size, hidden_size)
        self.gru = nn.GRU(hidden_size, hidden_size)
        self.out = nn.Linear(hidden_size, output_size)
        self.softmax = nn.LogSoftmax(dim = 1)

    def forward(self, input, hidden):
        output = self.embedding(input).view(1, 1, -1)
        output = F.relu(output)
        output, hidden = self.gru(output, hidden)
        output = self.softmax(self.out(output[0]))
        return output, hidden

    def initHidden(self):
        return torch.zeros(1, 1, self.hidden_size, device = device)
```

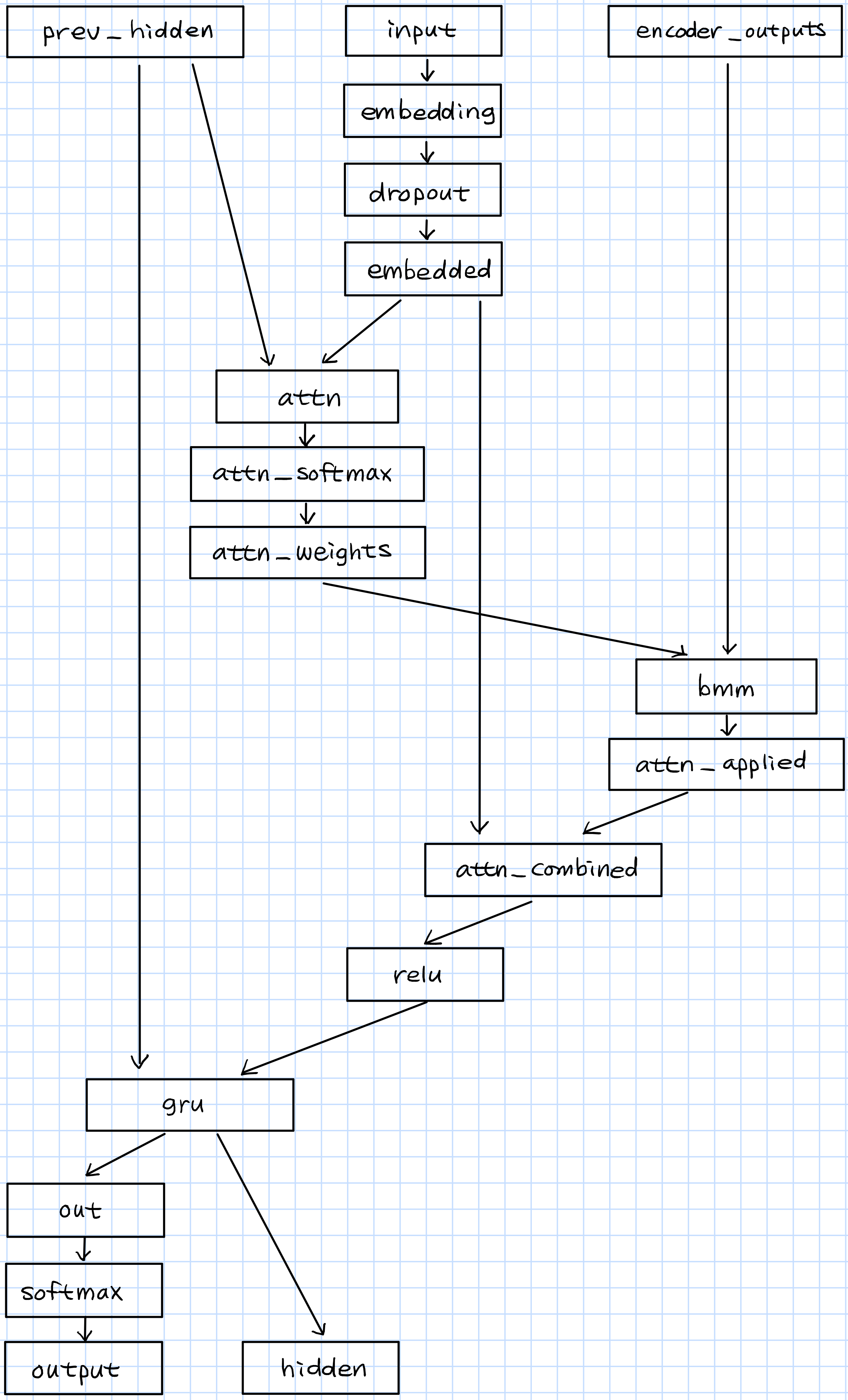
Attention Decoder

- Attention allows the decoder network to "focus" on a different part of the encoder's outputs for every step of the decoder's own outputs.



- the result should contain information about the specific part of the input sequence

→ help the decoder choose the right output words



have to choose
a maximum sentence length

- sentences of maximum length will use all the attention weights
- Shorter sentences will only use the first few.

```
class AttnDecoderRNN(nn.Module):
    def __init__(self, hidden_size, output_size, dropout_p = 0.1, max_length = MAX_LENGTH):
        super(AttnDecoderRNN, self).__init__()
        self.hidden_size = hidden_size
        self.output_size = output_size
        self.dropout_p = dropout_p
        self.max_length = max_length

        self.embedding = nn.Embedding(self.output_size, self.hidden_size)
        self.attn = nn.Linear(self.hidden_size * 2, self.max_length)
        self.attn_combine = nn.Linear(self.hidden_size * 2, self.hidden_size)
        self.dropout = nn.Dropout(self.dropout_p)
        self.gru = nn.GRU(self.hidden_size, self.hidden_size)
        self.out = nn.Linear(self.hidden_size, self.output_size)

    def forward(self, input, hidden, encoder_outputs):
        embedded = self.embedding(input).view(1, 1, -1)
        embedded = self.dropout(embedded)

        attn_weights = F.softmax(self.attn(torch.cat((embedded[0], hidden[0]), 1)), dim = 1)
        attn_applied = torch.bmm(attn_weights.unsqueeze(0), encoder_outputs.unsqueeze(0))

        output = torch.cat((embedded[0], attn_applied[0]), 1)
        output = self.attn_combine(output).unsqueeze(0)

        output = F.relu(output)
        output, hidden = self.gru(output, hidden)

        output = F.log_softmax(self.out(output[0]), dim = 1)
        return output, hidden, attn_weights

    def initHidden(self):
        return torch.zeros(1, 1, self.hidden_size, device = device)
```

Training

Preparing Training Data

- each pair, we will need an input tensor (indexes of the words in the input sentence)
  & target tensor (indexes of the words in the target sentence)
- while creating these vectors, we will append the EOS token to both sequences.

```
def indexesFromSentences (lang, sentence):
    return [lang.word2index[word] for word in sentence.split(' ')]

def tensorFromSentence (lang, sentence):
    indexes = indexesFromSentence (lang, sentence)
    indexes.append (EOS_token)
    return torch.tensor (indexes, dtype = torch.long, device = device).view (-1, 1)

def tensorsFromPair (pair)
    input_tensor = tensorFromSentence (input_lang, pair[0])
    target_tensor = tensorFromSentence (output_lang, pair[1])
    return (input_tensor, target_tensor)
```

Training the model

- Encoder
  - run the input sentence
  - Keep track of every output & latest hidden state.

- Decoder
  - given the <SOS> token as its first input
  - last hidden state of encoder as its first hidden state.

- Teacher forcing

: the concept of using real target outputs as each next input, instead of using the decoder's guess as the next input.

↓

- teacher-forced networks : coherent grammar, but not correct translation

why? it has learned to represent the output grammar & can "pick up" the meaning once the teacher tells it the first few words.

it has not properly learned how to create the sentence from the translation

```python
teacher_forcing_ratio = 0.5

def train (input_tensor, target_tensor, encoder, decoder,
          encoder_optimizer, decoder_optimizer, criterion, max_length = MAX_LENGTH):
    encoder_hidden = encoder.initHidden()

    encoder_optimizer.zero_grad()
    decoder_optimizer.zero_grad()

    input_length = input_tensor.size(0)
    target_length = target_tensor.size(0)

    encoder_outputs = torch.zeros(max_length, encoder.hidden_size, device = device)

    loss = 0

    for ei in range(input_length):
        encoder_output, encoder_hidden = encoder(input_tensor[ei], encoder_hidden)
        encoder_outputs[ei] = encoder_output[0,0]

    decoder_input = torch.tensor([[SOS_token]], device = device)
    decoder_hidden = encoder_hidden

    use_teacher_forcing = True if random.random() < teacher_forcing_ratio else False

    if use_teacher_forcing:
        for di in range(target_length):
            decoder_output, decoder_hidden, decoder_attention = decoder(
                decoder_input, decoder_hidden, encoder_outputs)
            loss += criterion(decoder_output, target_tensor[di])
            decoder_input = target_tensor[di]  # Teacher forcing
    else:
        # Without teacher forcing: use its own predictions as the next input
        for di in range(target_length):
            decoder_output, decoder_hidden, decoder_attention = decoder(
                decoder_input, decoder_hidden, encoder_outputs)
            topv, topi = decoder_output.topk(1)
            if topi.item() == EOS_token:
                decode_words.append('<EOS>')
                break
            else:
                decode_words.append(output_lang.index2word[topi.item()])

            decoder_input = topi.squeeze().detach()
        return decode_words, decoder_attentions[:di + 1]
```