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 (lang1)
        output_lang = Lang (lang2)
    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

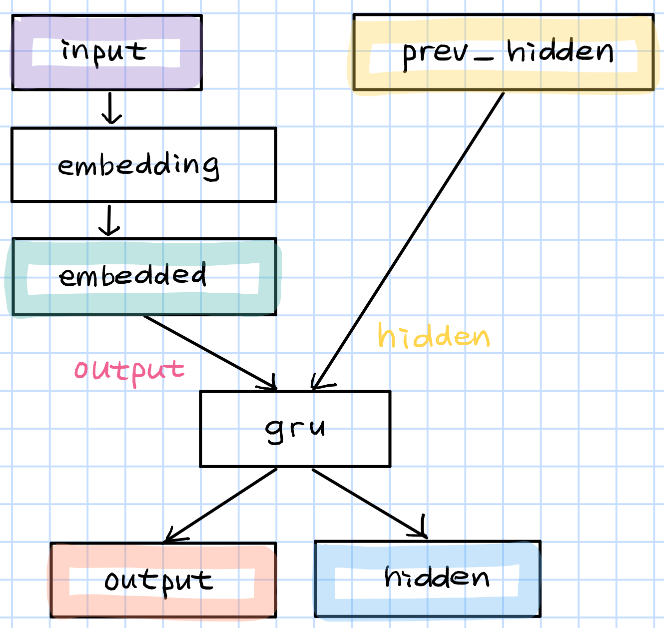
- RNN (Recurrent Neural Network)

  : 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



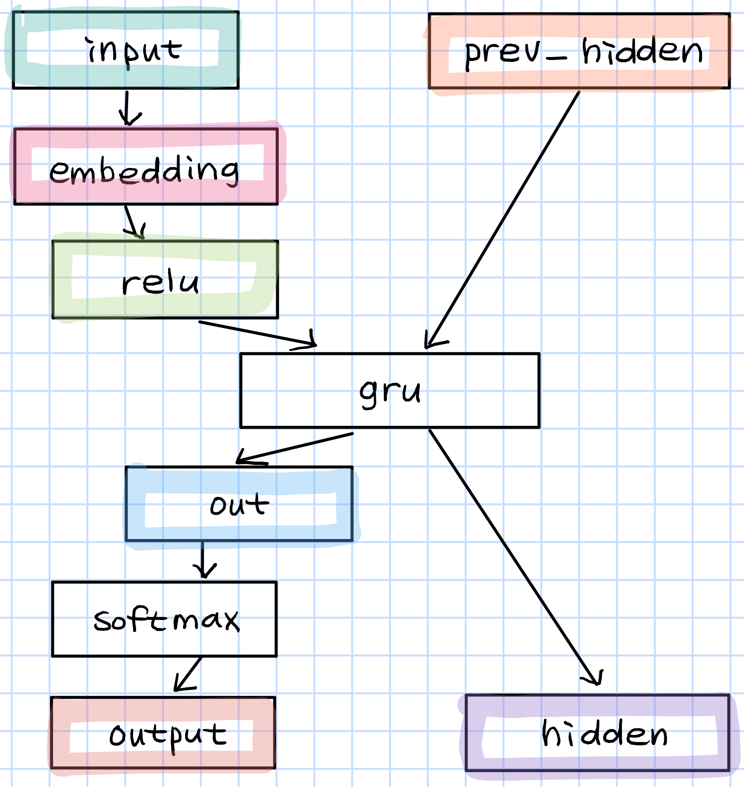

```
class EncoderRNN (nn.Module):
    def __init__(self, input_size, hidden_size):
        super(EncoderRNN, self).__init__()
        self.hidden_size = hidden_size

        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

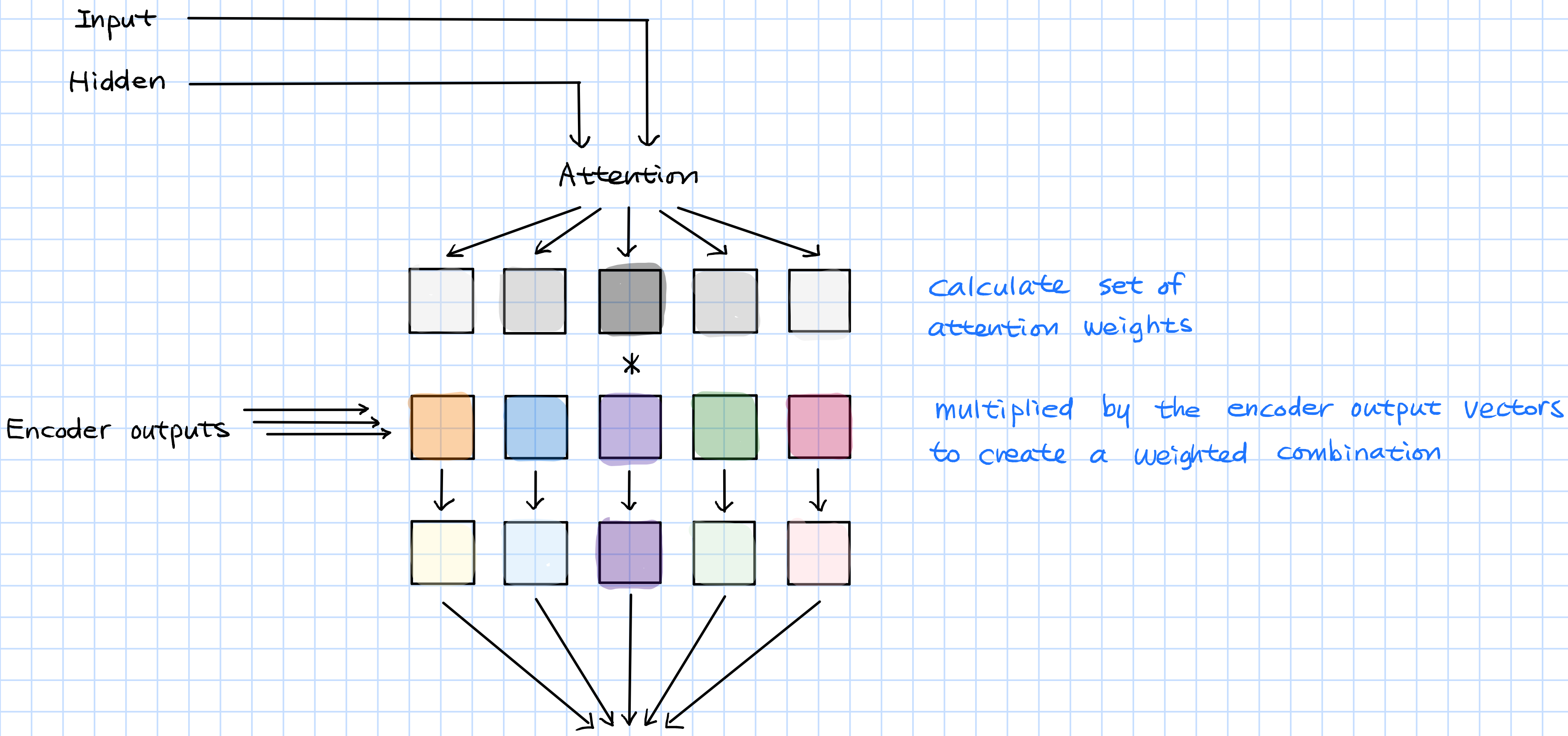
- use only last output of the encoder.
  sometimes called "context vector"
- Context vector is used as the initial hidden state of the decoder.
- At every step of decoding, the decoder is given an input token & hidden state.
  - initial input token : start-of-string <SOS>
  - first hidden state : context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



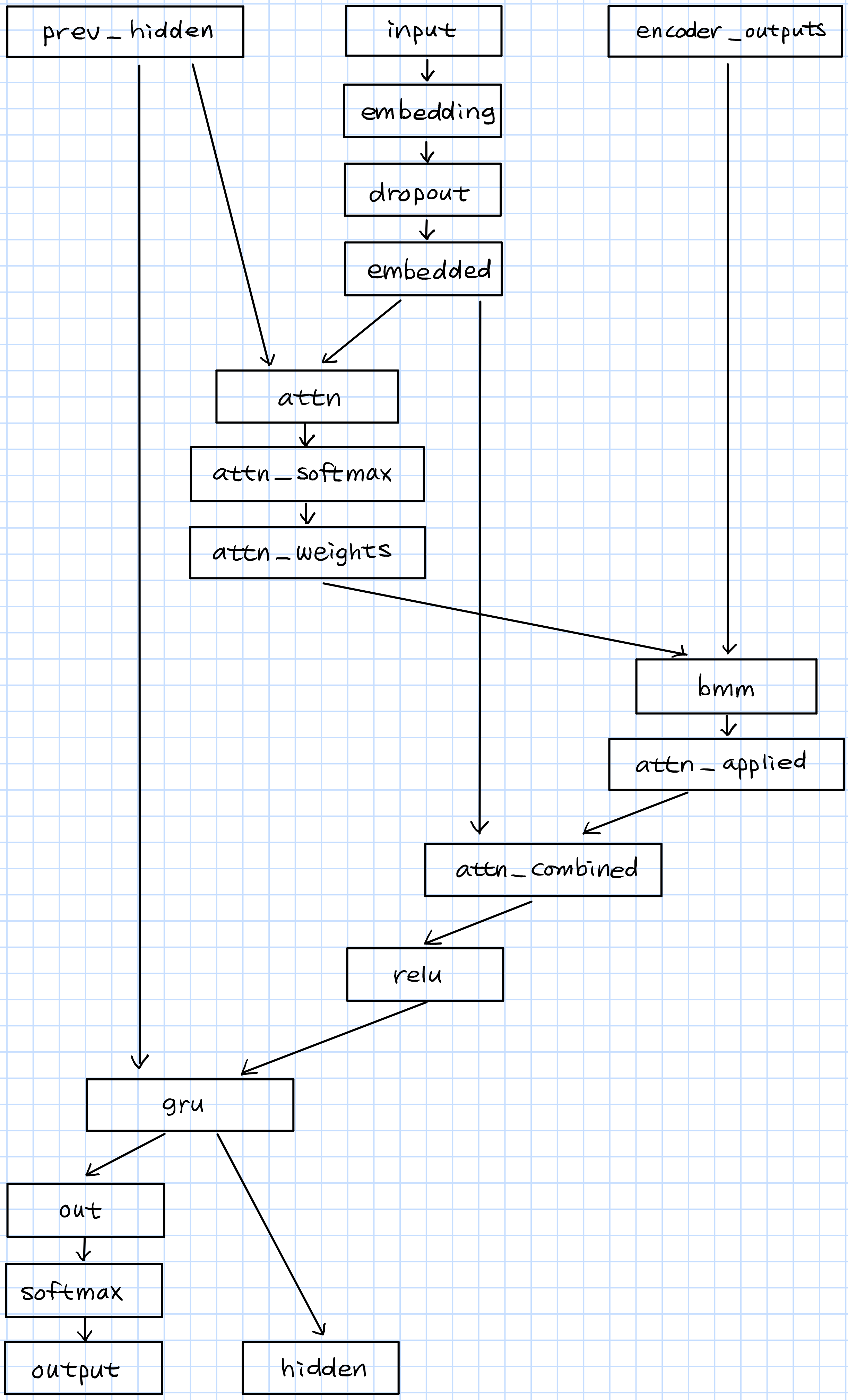

```
class DecoderRNN (nn.Module):
    def __init__ (self, hidden_size, output_size):
        super (DecoderRNN, self).__init__()
        self.hidden_size = hidden_size

        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.

```python
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

```
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)
            decoder_input = topi.squeeze().detach()  # detach from history as input

            loss += criterion(decoder_output, target_tensor[di])
            if decoder_input.item() == EOS_token:
                break
```

```
    loss.backward()

    encoder_optimizer.step()
    decoder_optimizer.step()

    return loss.item() / target_length

# helper function to print time elapsed and
# estimated time remaining given the current time and progress %
import time
import math

def asMinutes(s):
    m = math.floors(s / 60)
    s -= m * 60
    return '%dm %ds' % (m,s)

def timeSince(since, percent):
    now = time.time()
    s = now - since
    es = s / (percent)          → 전체 걸릴 시간
    rs = es - s                 → 남은 시간
    return '%s (- %s)' % (asMinutes(s), asMinutes(rs))
```

Whole training process

1. Start a timer
2. Initialize optimizer & criterion
3. Create set of training pairs
4. Start empty losses array for plotting.

call train many times!

```
def trainIters (encoder, decoder, n_iters, print_every = 1000,
                plot_every = 100, learning_rate = 0.01)
    start = time.time ()
    plot_losses = []
    print_loss_total = 0     # Reset every print_every
    plot_loss_total = 0      # Reset every plot_every

    encoder_optimizer = optim.SGD (encoder.parameters(), lr = learning_rate)
    decoder_optimizer = optim.SGD (decoder.parameters(), lr = learning_rate)
    training_pairs = [tensorFromPair (random.choice (pairs))
                      for i in range (n_iters)]
    criterion = nn.NLLLoss ()

    for iter in range (1, n_iters + 1):
        traing_pair = traing_pairs [iter - 1]
        input_tensor = training_pair [0]
        target_tensor = training_pair [1]

        loss = train (input_tensor, target_tensor, encoder, decoder,
                      encoder_optimizer, decoder_optimizer, criterion)
        print_loss_total += loss
        plot_loss_total += loss

        if iter % print_every == 0 :
            print_loss_avg = print_loss_total / print_every
            print_loss_total = 0
            print ('%s (%d %d%%) %.4f' % (timeSince (start, iter / n_iters), iter,
                                          iter / n_iters * 100, print_loss_avg))

        if iter % plot_every == 0 :
            plot_loss_avg = plot_loss_total / plot_every
            plot_losses.append (plot_loss_avg)
            plot_loss_total = 0

    showPlot (plot_losses)
```

Plotting results

```
import matplotlib.pyplot as plt
plt.switch_backend('agg')
import matplotlib.ticker as ticker
import numpy as np

def showPlot(points):
    plt.figure()
    fig, ax = plt.subplots()
    # this locator puts ticks at regular intervals
    loc = ticker.MultipleLocator(base=0.2)
    ax.yaxis.set_major_locator(loc)
    plt.plot(points)
```

Evaluation

- no target!
- simply feed the decoder's predictions back to itself for each step.
- word predicted ⇒ added to output string
- EOS token → stop there.
- store decoder's attention outputs for display later.

```
def evaluate (encoder, decoder, sentence, max_length = MAX_LENGTH) :
    with torch.no_grad():
        input_tensor = tensorFromSentence (input_lang, sentence)
        input_length = input_tensor.size() [0]
        encoder.hidden = encoder.initHidden ()

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

        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

        decoded_words = []
        decoder_attentions = torch.zeros (max_length, max_length)

        for di in range (max_length) :
            decoder_output, decoder_hidden, decoder_attention = decoder (
                decoder_input, decoder_hidden, encoder_outputs)
            decoder_attentions [di] = decoder_attention.data
            topv, topi = decoder_output.data.topk(1)
            if topi.item () == EOS_token :
                decoded_words.append ('<EOS>')
                break
            else :
                decoded_words.append (output_lang.index2word [topi.item()]

            decoder_input = topi.squeeze().detach()

        return decoded_words, decoder_attentions [:di+1]
```

```python
def evaluateRandomly (encoder, decoder, n=10):
    for i in range (n):
        pair = random.choice (pairs)
        print ('>', pair[0])
        print ('=', pair [1])
        output_words, attentions = evaluate (encoder, decoder, pair[0])
        output_sentence = ' '.join (output_words)
        print ('<', output_sentence)
        print ('')
```

Training & Evaluating

```python
hidden_size = 256
encoder1 = EncoderRNN (input_lang.n_words, hidden_size).to(device)
attn_decoder1 = AttnDecoderRNN (hidden_size, output_lang.n_words, dropout_p = 0.1).to(device)

trainIters (encoder1, attn_decoder1, 75000, print_every = 5000)

evaluateRandomly (encoder1, attn_decoder1)
```

*1 NLL Loss (Negative Log-Likelihood)

- output node 와 우리가 가진 데이터 분포 사이의 차이 : 크로스 엔트로피
- 이 차이만큼을 loss로 보고 이 loss에 대한 gradient를 구해 역전파하는 것이 "딥러닝"