Seq2Seq

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Introduction

Introduction

- **Although DNNs work well whenever large labeled training sets are available, they cannot be used to map sequences to sequences.**

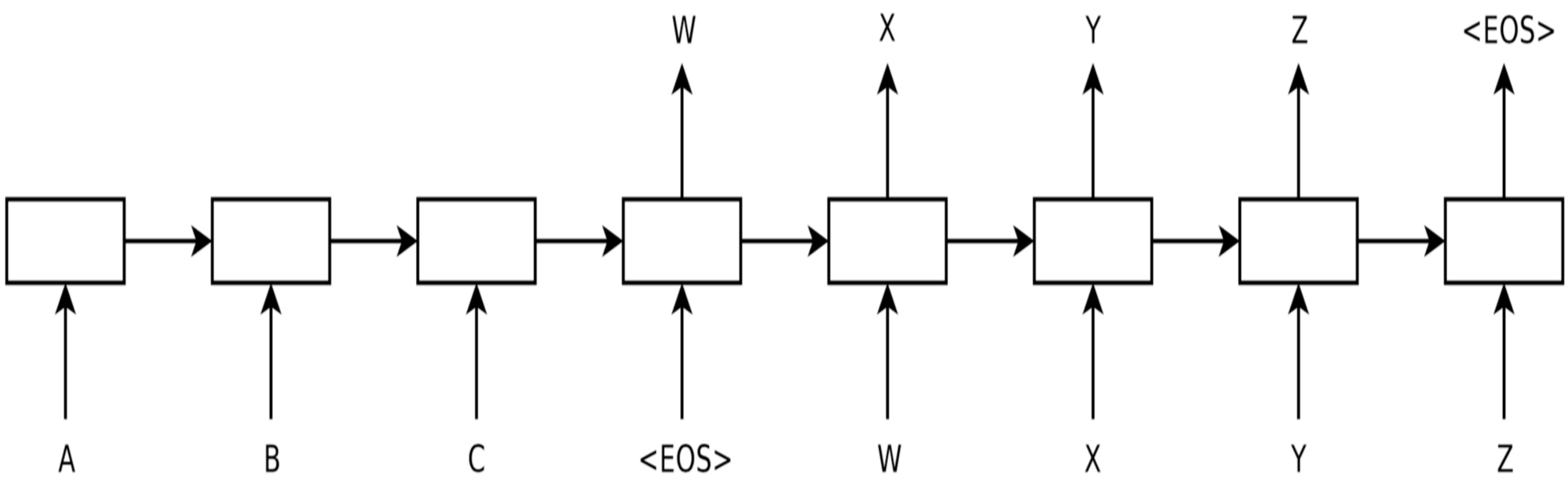
  (DNNs can only be applied to problems whose inputs and targets can be sensibly encoded with vectors of fixed dimensionality)

- **Many important problems are best expressed with sequences whose lengths are not know a-priori.**

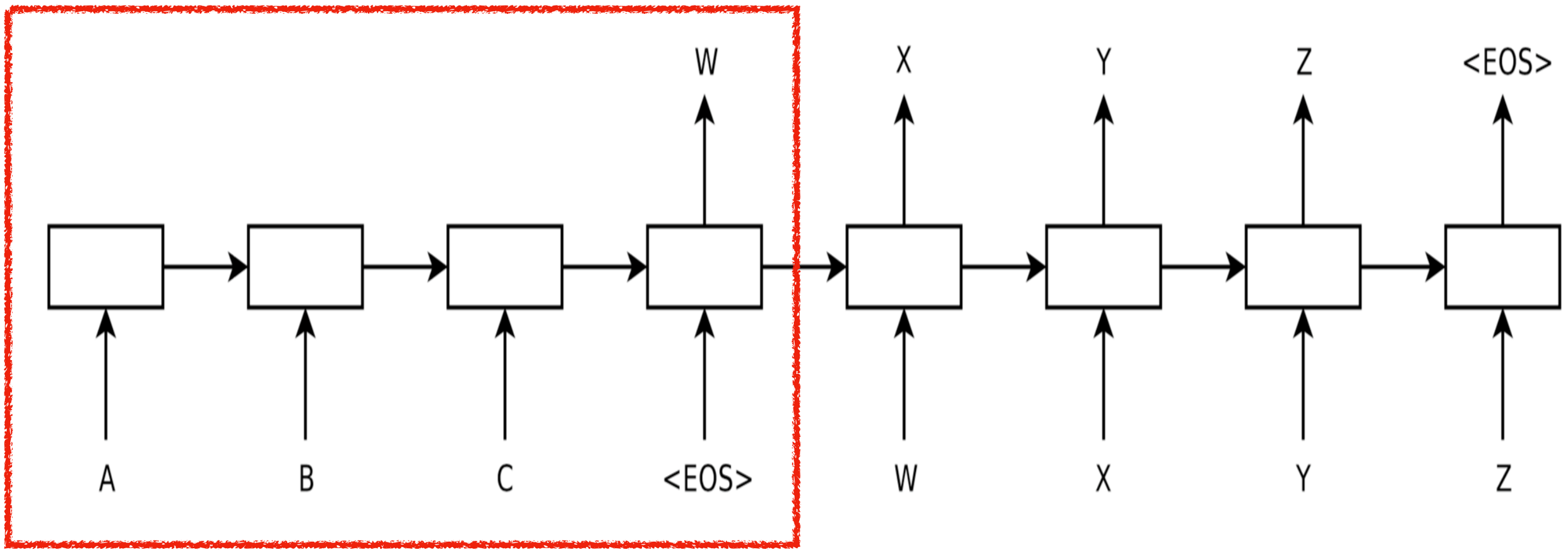
  (ex. speech recognition and machine translation)

Using LSTM

- **Using LSTM architecture, we can solve general sequence to sequence problems.**

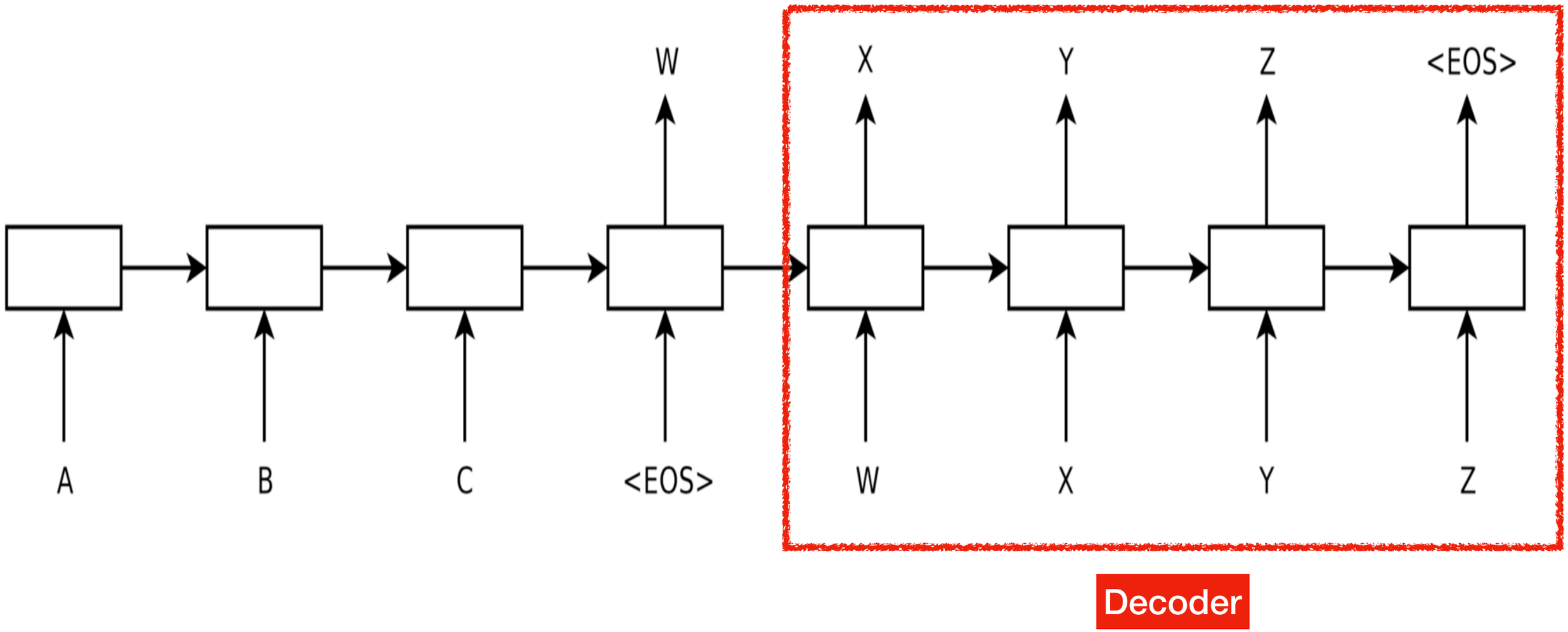


LSTM Encoder



- **read the input sequence, one time step at a time, to obtain large fixed-dimensional vector representation.**

LSTM Decoder



- **extract the output sequence from that vector**

Related Works

- ***Kalchbrenner and Blunsom***

  - who were the first map the entire input sentence to vector

- ***Kyung-Hyun, Cho***

  - used only for rescoring hypotheses produced by phase-based System

- ***Graves***

  - introduce a novel differentiable attention mechanism that allow neural networks to focus on different parts of their input.

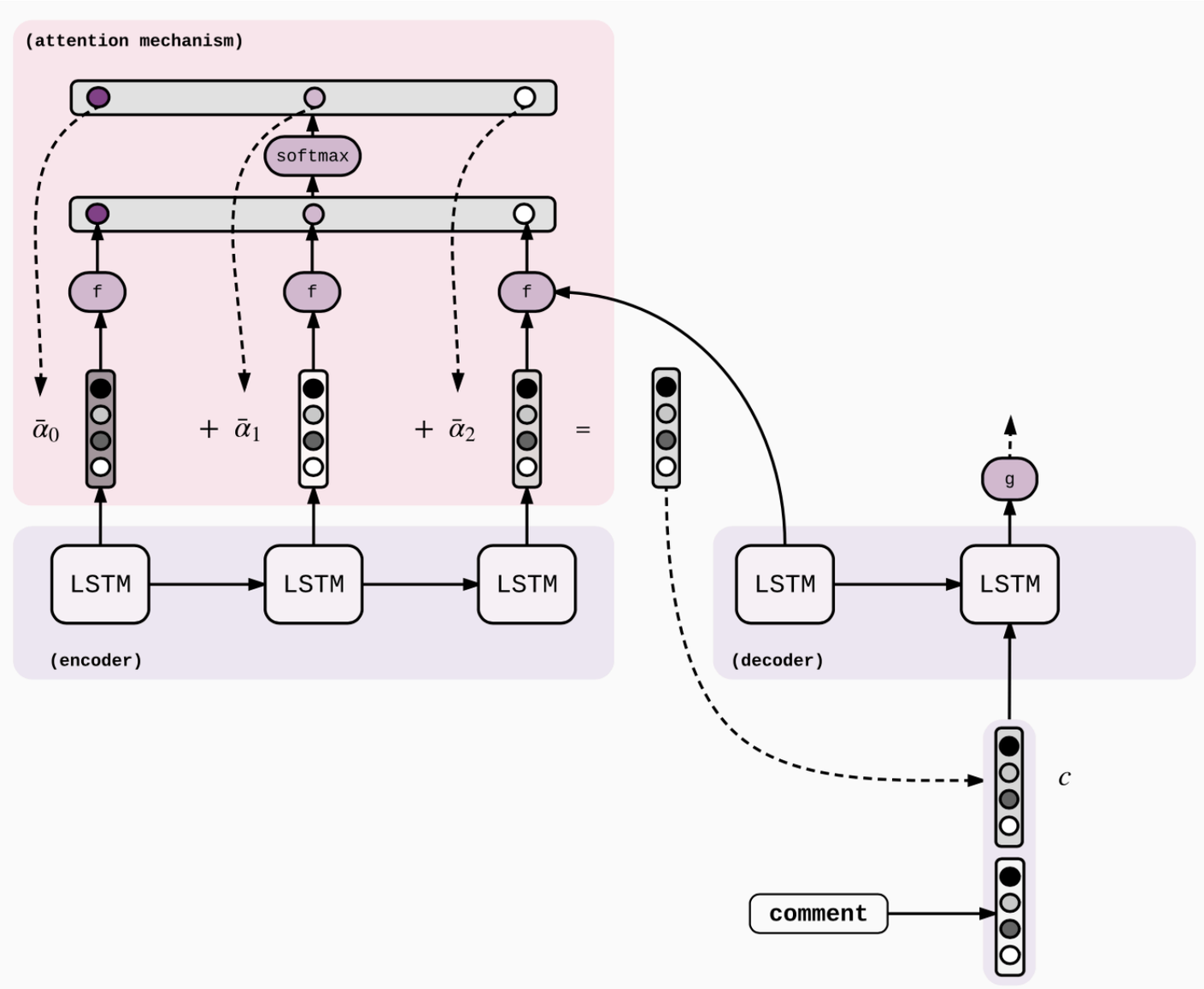
- ***Bahdanau***

  - an elegant variant of attention mechanism was successfully applied to machine translation

With Attention

$$
\begin{aligned}
h_t &= \text{LSTM}(h_{t-1}, [w_{i_{t-1}}, c_t]) \\
s_t &= g(h_t) \\
p_t &= \text{softmax}(s_t) \\
i_t &= \text{argmax}(p_t)
\end{aligned}
$$

$$
\begin{aligned}
\alpha_{t'} &= f(h_{t-1}, e_{t'}) \in \mathbb{R} \qquad \text{for all } t' \\
\bar{\alpha} &= \text{softmax}(\alpha) \\
c_t &= \sum_{t'=0}^{n} \bar{\alpha}_{t'} e_{t'}
\end{aligned}
$$



Attention Mechanism

The Model

RNN model

RNN equation :

$$
\begin{aligned}
h_t &= \operatorname{sigm}\left(W^{\mathrm{hx}} x_t + W^{\mathrm{hh}} h_{t-1}\right) \\
y_t &= W^{\mathrm{yh}} h_t
\end{aligned}
$$

- **RNN can easily map sequences to sequences whenever the alignment between the inputs the outputs is known ahead of time**

- **The simplest strategy for general sequence learning is to map the input sequence to a fixed-sized vector using one RNN, and then to map the vector to the target sequence with another RNN , Kyung-Hyun, Cho**

- **Because of long term dependencies, LSTM is better than RNN**

LSTM model

The goal of the LSTM is to estimate the conditional probability $p(y_1, \ldots, y_{T'}|x_1, \ldots, x_T)$ where $(x_1, \ldots, x_T)$ is an input sequence and $y_1, \ldots, y_{T'}$ is its corresponding output sequence whose length T' may differ from T. The LSTM computes this conditional probability by first obtaining the fixed-dimensional representation v of the input sequence $(x_1, \ldots, x_T)$ given by the last hidden state of the LSTM, and then computing the probability of $y_1, \ldots, y_{T'}$ with a standard LSTM-LM formulation whose initial hidden state is set to the representation v of $x_1, \ldots, x_T$:

$$p(y_1, \ldots, y_{T'}|x_1, \ldots, x_T) = \prod_{t=1}^{T'} p(y_t|v, y_1, \ldots, y_{t-1}) \quad (1)$$

In this equation, each $p(y_t|v, y_1, \ldots, y_{t-1})$ distribution is represented with a softmax over all the words in the vocabulary. We use the LSTM formulation from Graves [10]. Note that we require that each sentence ends with a special end-of-sentence symbol "<EOS>", which enables the model to define a distribution over sequences of all possible lengths. The overall scheme is outlined in figure 1, where the shown LSTM computes the representation of "A", "B", "C", "<EOS>" and then uses this representation to compute the probability of "W", "X", "Y", "Z", "<EOS>".

Differences

Our actual models differ from the above description in three important ways. First, we used two different LSTMs: one for the input sequence and another for the output sequence, because doing so increases the number model parameters at negligible computational cost and makes it natural to train the LSTM on multiple language pairs simultaneously [18]. Second, we found that deep LSTMs significantly outperformed shallow LSTMs, so we chose an LSTM with four layers. Third, we found it extremely valuable to reverse the order of the words of the input sentence. So for example, instead of mapping the sentence a, b, c to the sentence α, β, γ, the LSTM is asked to map c, b, a to α, β, γ, where α, β, γ is the translation of a, b, c. This way, a is in close proximity to α, b is fairly close to β, and so on, a fact that makes it easy for SGD to "establish communication" between the input and the output. We found this simple data transformation to greatly improve the performance of the LSTM.

Experiments

Dataset details

- **WMT’14 English to French dataset.**
- **trained our models on a subset of 12M sentences consisting of 348M French words and 304M English words.**
- **typical neural language models rely on a vector representation for each word, we used a fixed vocabulary for both languages.**
- **160,000 of the most frequent words for the source language and 80,000 of the most frequent words for the target language.**

Decoding & Rescoring

Training objective: maximizing the log probability

$$1/|\mathcal{S}| \sum_{(T,S)\in\mathcal{S}} \log p(T|S)$$

Once training is complete, produce translations by finding the most likely translation according to the LSTM :

$$\hat{T} = \arg\max_{T} p(T|S)$$

Beam Search

keep track of k hypothesis, k is beam size

$$\mathcal{H}_t := \{(w_1^1, \ldots, w_t^1), \ldots, (w_1^k, \ldots, w_t^k)\}$$

if k = 2 :

$$\mathcal{H}_2 := \{(\text{comment vas}), (\text{comment tu})\}$$

$$\mathcal{C}_{t+1} := \bigcup_{i=1}^{k} \{(w_1^i, \ldots, w_t^i, 1), \ldots, (w_1^i, \ldots, w_t^i, V)\}$$

Let’s See With Code !

Prepare Data

```
def prepareData(lang1, lang2, reverse=True):
    input_lang, output_lang, pairs = readLangs(lang1, lang2, reverse)
    print("Read %s sentence pairs" % len(pairs))
    #pairs = filterPairs(pairs)
    print("pairs: ", 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('user', 'nuguri', True)
```

Reverse !

```
def readLangs(lang1, lang2, reverse=True):
    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')

    # print('lines: ',lines)

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

Encoder RNN

```
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
        self.gru.flatten_parameters()
        output, hidden = self.gru(output, hidden)
        return output, hidden

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

Decoder RNN

```
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

```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

```
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:
    # Teacher forcing: Feed the target as the next input
    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
```

```
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 = [tensorsFromPair(random.choice(pairs))
                      for i in range(n_iters)]
    criterion = nn.NLLLoss()

    for iter in range(1, n_iters + 1):
        training_pair = training_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)
```

evaluate

```
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)  # SOS

        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]
```

```
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('')
```

```
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)

# model save.

try:
    if not (os.path.isdir('model')):
        os.makedirs(os.path.join('model'))
except OSError as e:
    if e.errno != errno.EEXIST:
        print("Failed to create difrectory")
        raise
```