BiRNN

contribution

在这篇论文之前，对于处理不定长的时间序列的数据使用的方法主要有TDNN和RNN，作者在各种问题上的实验表明RNN在处理这些数据上有着更大的优势，但传统的单向RNN只能获取到`left-to-right`的单向信息，作者通过加入反向的RNN，使得网络可以同时获取到双向的信息，进而提高模型的准确度。

如下图，传统的MLP只适用于固定长度的数据，TDNN通过设定一个窗口，截取一定长度的数据，一定程度上解决了不定长数据的问题，但网络获取的信息受限于窗口的大小，RNN则通过`state`的传递，理论上可以获取到整个序列的信息，但实际上RNN对于长序列的处理并不好，通过加入`delay`一定程度上可以改善模型，但这一问题依然存在，因此作者通过结果双向的RNN尝试解决这一问题

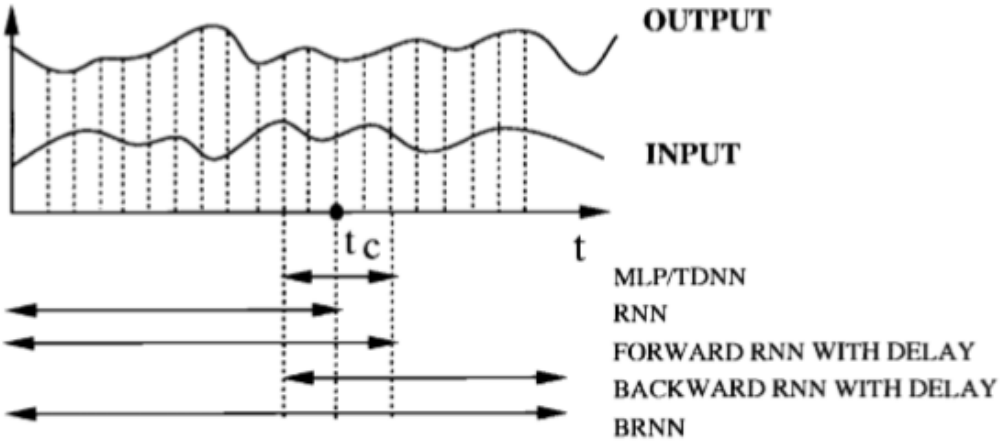


Fig. 2. Visualization of the amount of input information used for prediction by different network structures.

method

传统的RNN如下图所示

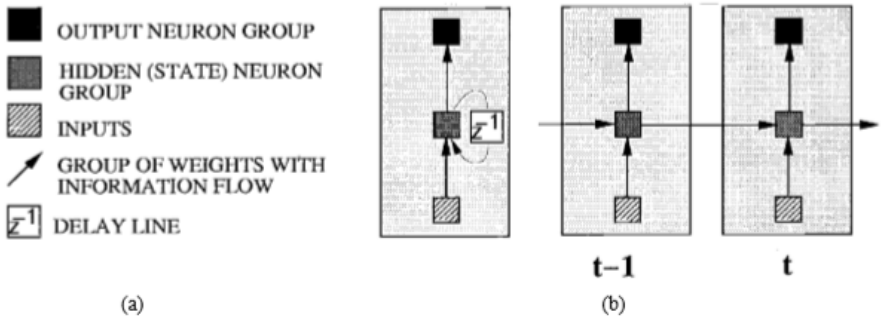


Fig. 1. General structure of a regular unidirectional RNN shown (a) with a delay line and (b) unfolded in time for two time steps.

通过加入反向的RNN，模型如下图所示

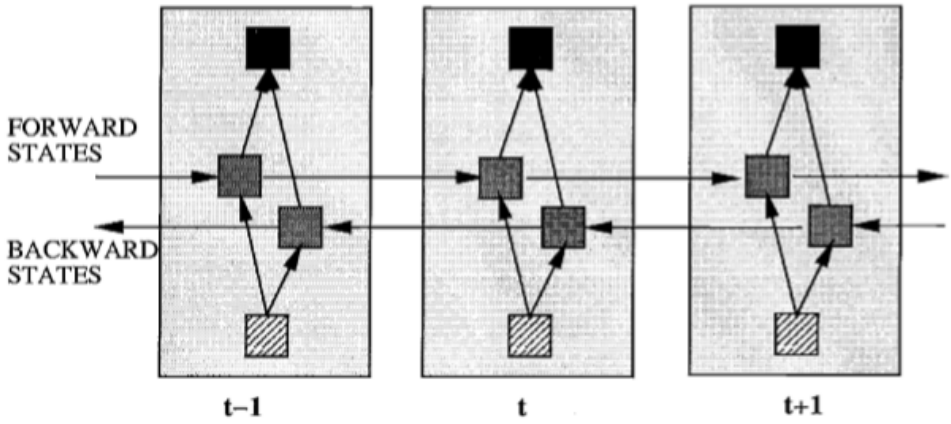


Fig. 3. General structure of the bidirectional recurrent neural network (BRNN) shown unfolded in time for three time steps.

`t`时段的输入由`Forward States`和`Backward States`的权重处理后得到两个结果，两个结果经过线性变化（可通过训练得出相应的权重）得到`t`时段的输出，前向与反向的`state`是单向传递的，相互之间没有连接

训练时，先后正反向计算RNN State，然后根据线性变化得到output

反向传播则先对output求导，然后先后对正反向求导，最后更新权重

advantages and disadvantages

由于RNN在梯度传播中的梯度消失/爆炸，RNN只能获取到短的时间关系，BiRNN通过加入反向RNN的方法虽然让网络得以利用反向的信息，但并没有解决RNN无法获取长序列信息的问题

而且在用双向RNN的时候，需要完整的序列，不能一边接收序列一边处理

LSTM

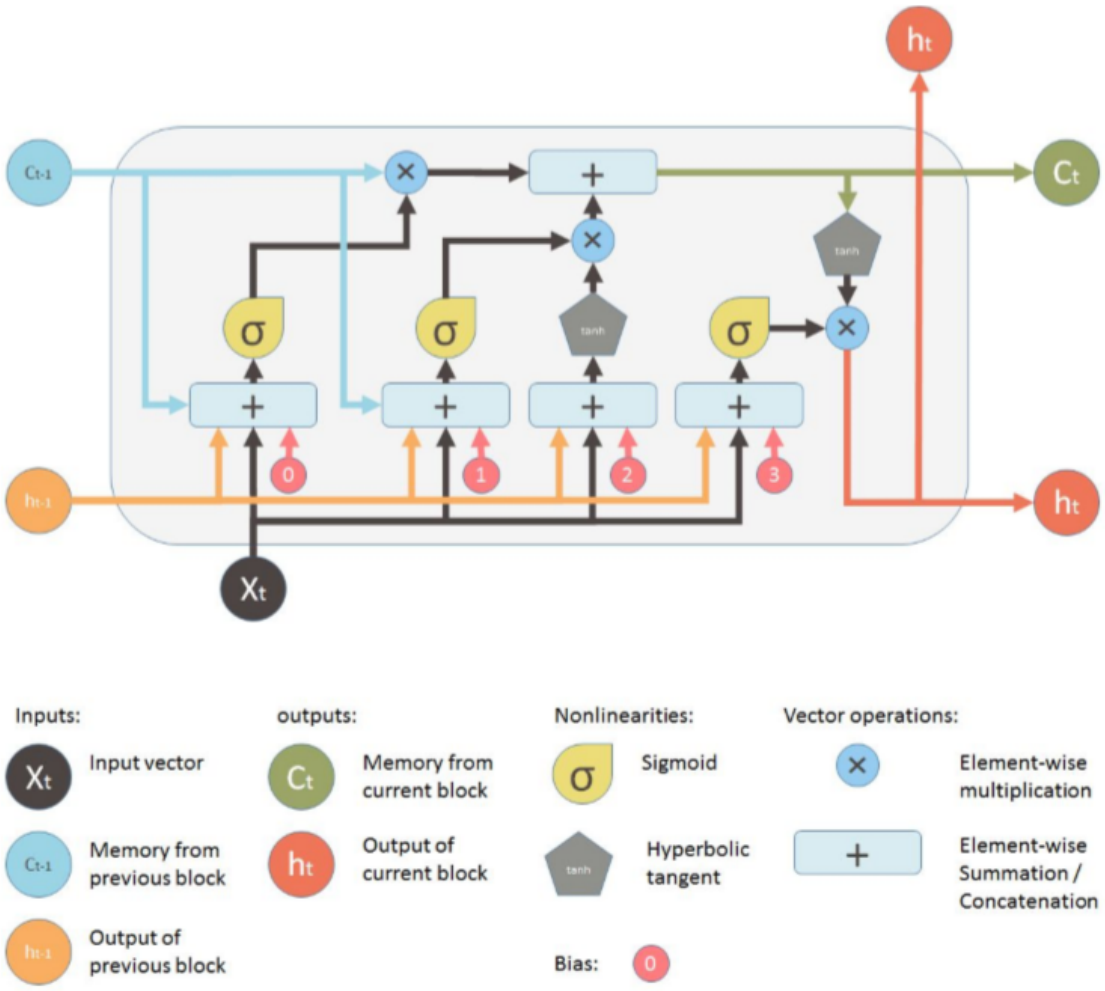
contribution

针对RNN无法获取长序列信息的问题，LSTM通过改进RNN基础单元的结构，通过增加几种门结构，使得LSTM可以控制信息的记忆与遗忘

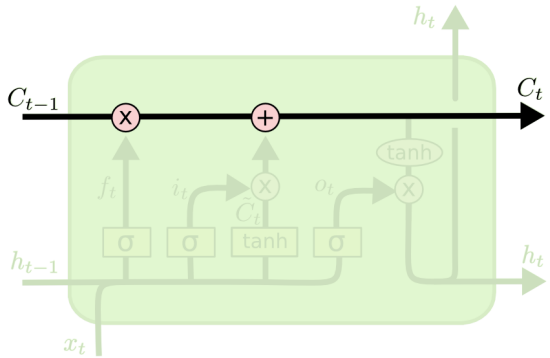
method

以下参考Understanding LSTM Networks，部分图也来源于此

LSTM由几种门结构组合而成，整体的结构如下图

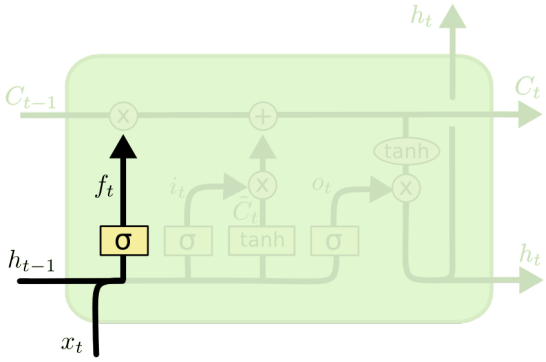


最上方的为细胞状态，LSTM通过门结构来去除或添加信息到细胞状态



Forget Gate

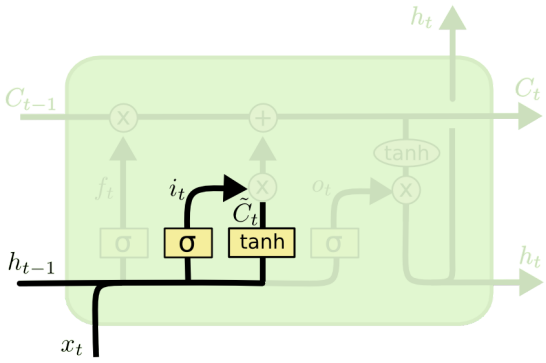
用于决定从细胞状态中丢弃什么信息，公式如下，`Forget Gate`以h_{t-1}和x_t为输入，经过线性变换后，用σ决定信息保留的程度，1表示完全保留，0表示完全舍弃



$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \; + \; b_f\right)$$

Input Gate

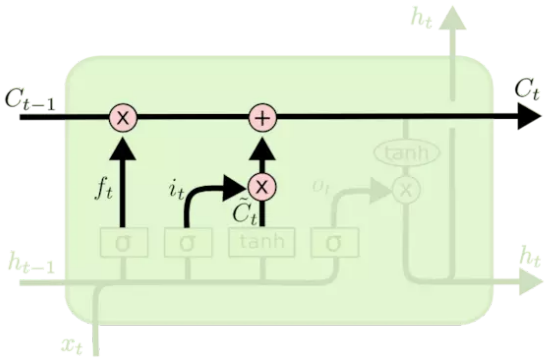
用于决定向细胞状态中增加什么信息，公式如下，同样以h_{t-1}和x_t为输入，$\tilde{C}_t$代表新的信息，i_t则用于控制新信息添加的程度



$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \; + \; b_i\right)$$
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \; + \; b_C)$$

Memory Update

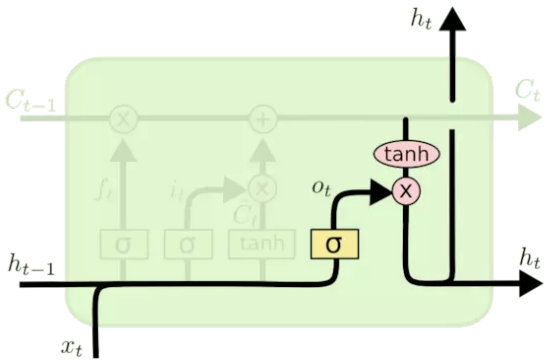
在通过`Forget Gate`和`Input Gate`得到需要丢弃和增加的信息之后，细胞状态更新的公式如下所示



$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

Output Gate

用于决定输出的`hidden state`，公式如下，首先通过σ控制输出的部分，然后再将新的细胞状态进过`tanh`处理与σ门的输出相乘



$$o_t = \sigma\left(W_o \; [h_{t-1}, x_t] \; + \; b_o\right)$$
$$h_t = o_t * \tanh\left(C_t\right)$$

advantages and disadvantages

优点：

- 门结构可以有效的使网络学习到长时序的依赖关系

缺点：

- 运算速度较GRU慢
- 虽然改进了RNN对于长序列处理的问题，但依旧没有完全解决，而且还是会有梯度爆炸的问题

GRU

contribution

与LSTM类似，都是为了解决RNN无法获取长序列信息的问题，另外这篇文章还提出了`Encoder-Decoder`模型，用于处理机器翻译等问题

method

Encoder-Decoder

`Encoder-Decoder`模型由两个RNN组成，`Encoder`部分就是正常的RNN模型，在读取完整个句子后输出一个C，作为`Decoder`的输入，`Decoder`的`hidden state`计算公式如下，y就是输出的序列

$$h_{<t>} = f(h_{<t-1>}, y_{t-1}, c)$$

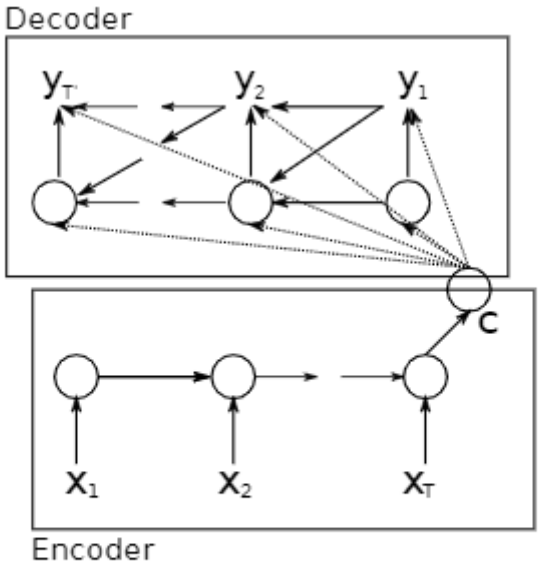
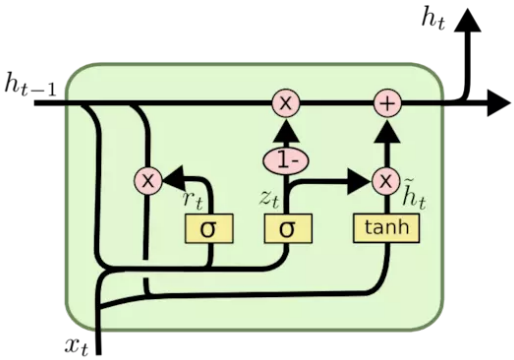


Figure 1: An illustration of the proposed RNN Encoder–Decoder.

GRU

GRU有两个门结构`Reset Gate`和`Update Gate`，总体结构如下



$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$
$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$
$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$
$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

Reset Gate

`Reset Gate`公式如下，通过h_{t-1}和x_t决定要将多少过去的信息遗忘

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t])$$

Update Gate

`Update Gate`公式如下，通过h_{t-1}和x_t决定要将多少过去的信息传递下去

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t])$$

Output

最后的`Output`公式如下，通过r_t控制记忆的内容，然后再通过z_t得到最终输出的状态，类似LSTM的`Memory Update`，但GRU将`cell state`和`hidden state`合并了起来

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$
$$\tilde{h}_t = tanh(W \cdot [r_t * h_{t-1}, x_t])$$

advantages and disadvantages

简化了LSTM中复杂的结构，而且性能与LSTM接近

seq2seq

contribution

使用将两个RNN组合起来的方法（类似于`Encoder-Decoder`），很好的解决了传统深度神经网络无法处理输入输出都不定长的`seq2seq`问题

method

类似于`Encoder-Decoder`，本文使用的网络也有类似的结构，通过两段LSTM的组合，完成`seq2seq`的任务，模型的左边（直到输入`<EOS>`）相当于`Encoder`，右侧则相当于`Decoder`，模型输入ABC和结束符`<EOS>`，然后解码出WXYZ直到模型输出结束符

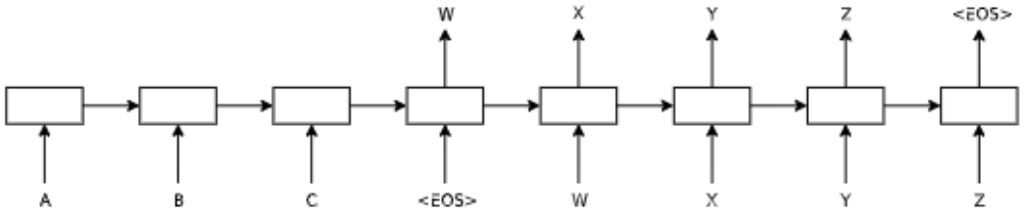


Figure 1: Our model reads an input sentence "ABC" and produces "WXYZ" as the output sentence. The model stops making predictions after outputting the end-of-sentence token. Note that the LSTM reads the input sentence in reverse, because doing so introduces many short term dependencies in the data that make the optimization problem much easier.

一些细节

- 深层网络比浅层网络好（文中用了4层LSTM）
- LSTM虽然没有梯度消失的问题，但是还会有梯度爆炸，这个模型对大梯度进行了缩放
- 将输入倒序会提升表现（或许是因为两个语言翻译的时候，被译句前面几个单词经常对应译句的后几个单词）
- 搜索时采用`beam search`，但`beam size`对模型准确度影响不大，当`beam size`等于2时，模型基本达到最优准确度

advantages and disadvantages

优点：

- 实现了端到端的`seq2seq`网络

缺点：

- 多层LSTM的组合使得网络的参数很多，运行效率低，且RNN也不能进行并行计算

Transformer

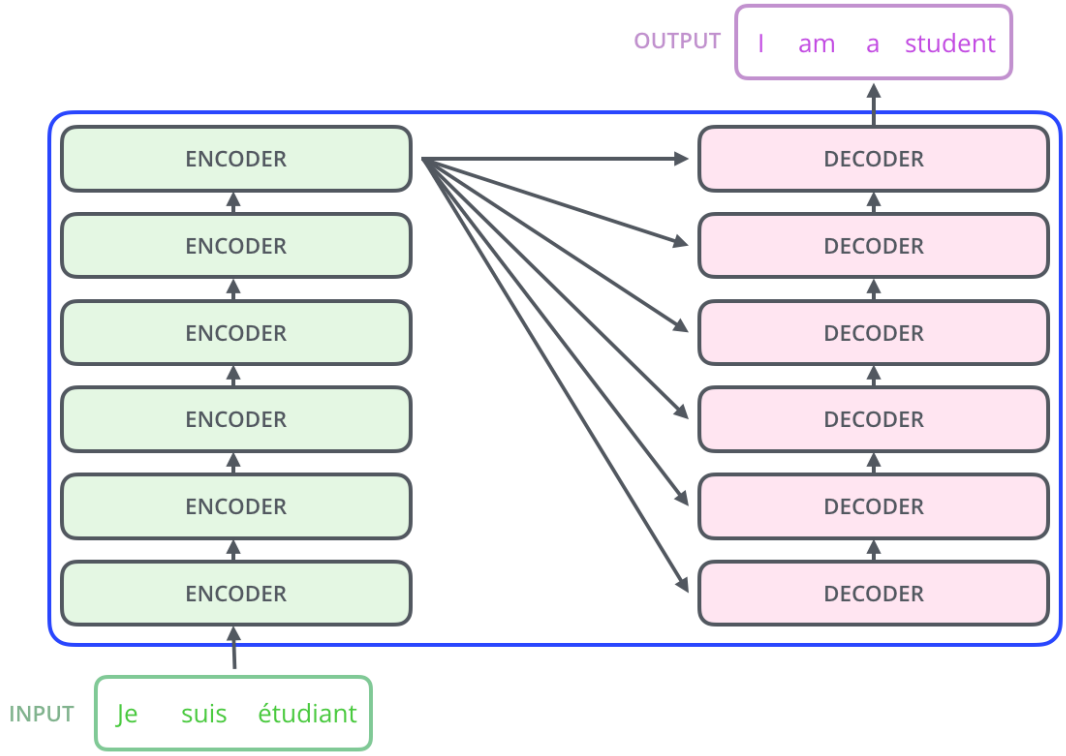
contribution

完全抛弃了传统的RNN和CNN结构

method

之前有看过该论文而且留下了笔记，所以下面的内容都是之前笔记的内容

大多数NLP任务都是`Encoder-decoder`的结构，比如机器翻译，input通过几层`Encoder`后再经过`Decoder`输出



一个标准的`Encoder-decoder`结构代码如下：

```
class EncoderDecoder(nn.Module):
    """
    A standard Encoder-Decoder architecture. Base for this and many
    other models.
    """
    def __init__(self, encoder, decoder, src_embed, tgt_embed, generator):
        super(EncoderDecoder, self).__init__()
        self.encoder = encoder
        self.decoder = decoder
        self.src_embed = src_embed
        self.tgt_embed = tgt_embed
        self.generator = generator

    def forward(self, src, tgt, src_mask, tgt_mask):
        "Take in and process masked src and target sequences."
        return self.decode(self.encode(src, src_mask), src_mask,
                           tgt, tgt_mask)

    def encode(self, src, src_mask):
        return self.encoder(self.src_embed(src), src_mask)

    def decode(self, memory, src_mask, tgt, tgt_mask):
        return self.decoder(self.tgt_embed(tgt), memory, src_mask, tgt_mask)


class Generator(nn.Module):
    "Define standard linear + softmax generation step."
    def __init__(self, d_model, vocab):
        super(Generator, self).__init__()
        self.proj = nn.Linear(d_model, vocab)

    def forward(self, x):
        return F.log_softmax(self.proj(x), dim=-1)
```

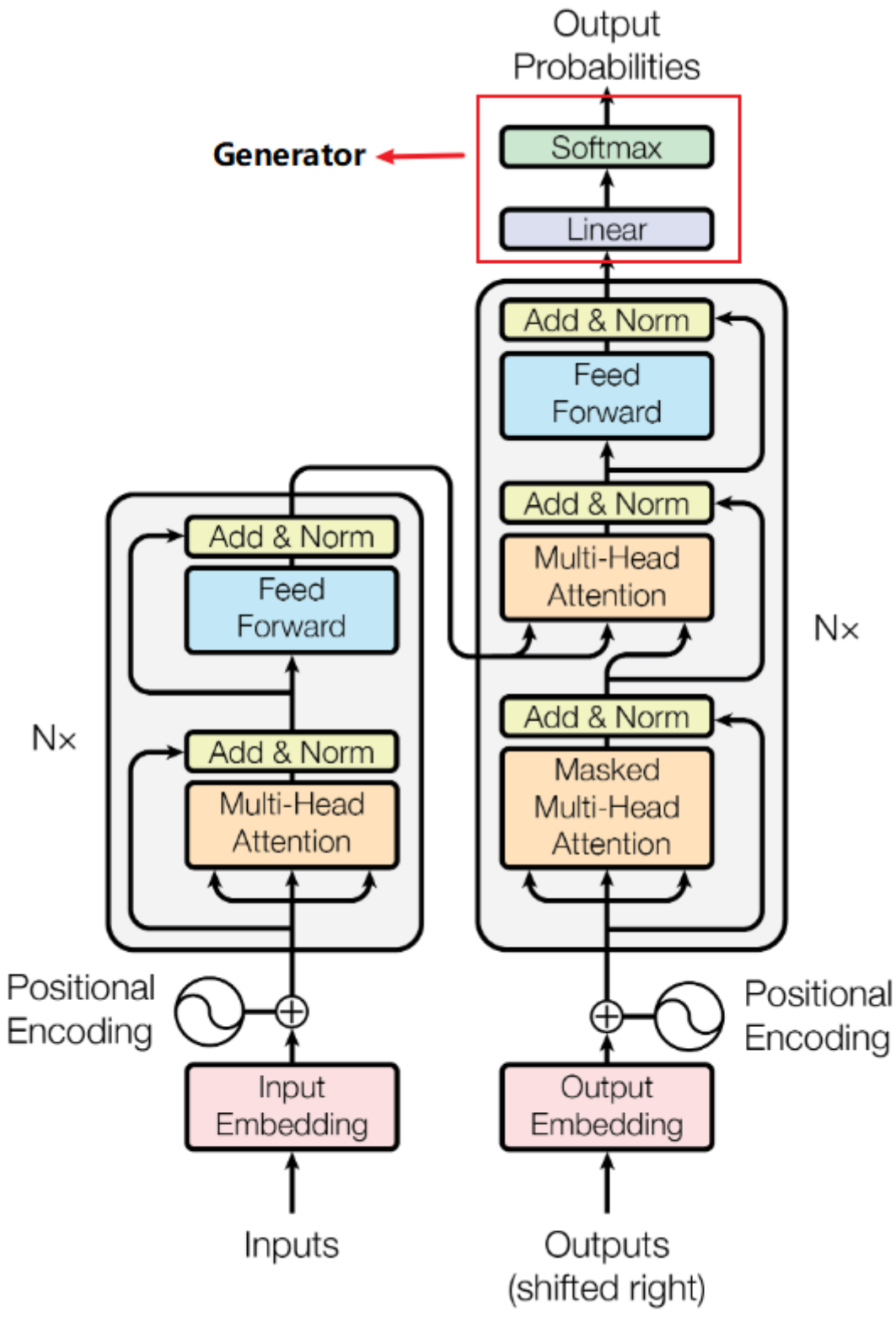


Figure 1: The Transformer - model architecture.

在Attention模型中，每层 `Encoder` 都有两部分，输入首先经过 `Attention` 层，第二层则是一个简单的全连接层，每层 `Encoder` 都会有类似残差网络的跨层连接，`Norm` 是 `Layer Normalization` ，所以每层的 `Output` 就是$LayerNorm(x + Sublayer(x))$

`Decoder` 结构类似 `Encoder` ，不过在中间多加了一层 `Attention` 用于处理 `Encoder` 的 `Output`

Encoder和Decoder的代码

Encoder

```
def clones(module, N):
    "Produce N identical layers."
    return nn.ModuleList([copy.deepcopy(module) for _ in range(N)])

class Encoder(nn.Module):
    "Core encoder is a stack of N layers"
    def __init__(self, layer, N):
        super(Encoder, self).__init__()
        self.layers = clones(layer, N)
        self.norm = LayerNorm(layer.size)

    def forward(self, x, mask):
        "Pass the input (and mask) through each layer in turn."
        for layer in self.layers:
            x = layer(x, mask)
        return self.norm(x)

class LayerNorm(nn.Module):
    "Construct a layernorm module (See citation for details)."
    def __init__(self, features, eps=1e-6):
        super(LayerNorm, self).__init__()
        self.a_2 = nn.Parameter(torch.ones(features))
        self.b_2 = nn.Parameter(torch.zeros(features))
        self.eps = eps

    def forward(self, x):
        mean = x.mean(-1, keepdim=True)
        std = x.std(-1, keepdim=True)
        return self.a_2 * (x - mean) / (std + self.eps) + self.b_2


class SublayerConnection(nn.Module):
    """
    A residual connection followed by a layer norm.
    Note for code simplicity the norm is first as opposed to last.
    """
    def __init__(self, size, dropout):
        super(SublayerConnection, self).__init__()
        self.norm = LayerNorm(size)
        self.dropout = nn.Dropout(dropout)

    def forward(self, x, sublayer):
        "Apply residual connection to any sublayer with the same size."
        return x + self.dropout(sublayer(self.norm(x)))


class EncoderLayer(nn.Module):
    "Encoder is made up of self-attn and feed forward (defined below)"
    def __init__(self, size, self_attn, feed_forward, dropout):
        super(EncoderLayer, self).__init__()
        self.self_attn = self_attn
        self.feed_forward = feed_forward
        self.sublayer = clones(SublayerConnection(size, dropout), 2)
        self.size = size
```

```
    def forward(self, x, mask):
        "Follow Figure 1 (left) for connections."
        x = self.sublayer[0](x, lambda x: self.self_attn(x, x, x, mask))
        return self.sublayer[1](x, self.feed_forward)
```

Decoder

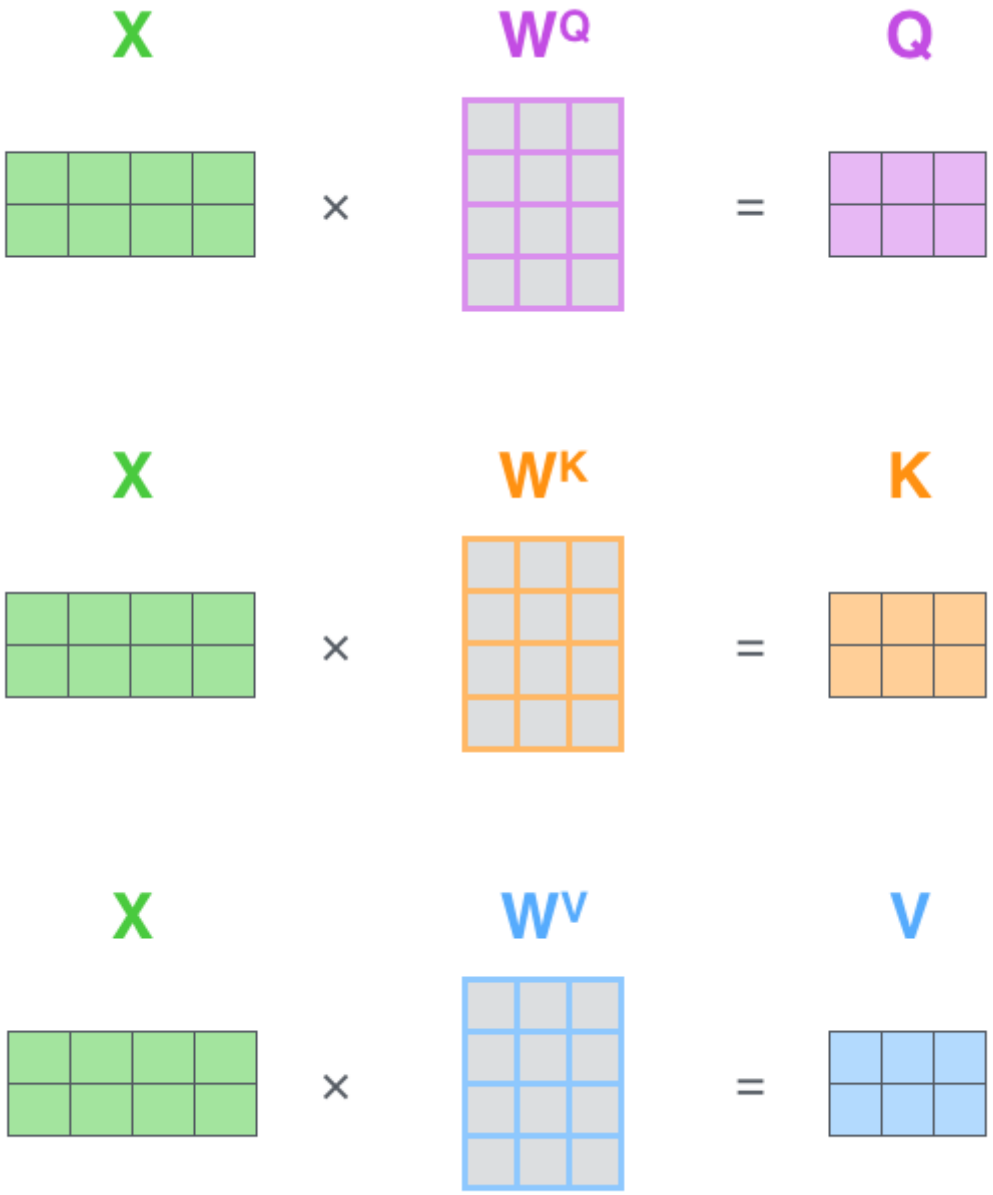
```
class Decoder(nn.Module):
    "Generic N layer decoder with masking."
    def __init__(self, layer, N):
        super(Decoder, self).__init__()
        self.layers = clones(layer, N)
        self.norm = LayerNorm(layer.size)

    def forward(self, x, memory, src_mask, tgt_mask):
        for layer in self.layers:
            x = layer(x, memory, src_mask, tgt_mask)
        return self.norm(x)


class DecoderLayer(nn.Module):
    "Decoder is made of self-attn, src-attn, and feed forward (defined below)"
    def __init__(self, size, self_attn, src_attn, feed_forward, dropout):
        super(DecoderLayer, self).__init__()
        self.size = size
        self.self_attn = self_attn
        self.src_attn = src_attn
        self.feed_forward = feed_forward
        self.sublayer = clones(SublayerConnection(size, dropout), 3)

    def forward(self, x, memory, src_mask, tgt_mask):
        "Follow Figure 1 (right) for connections."
        m = memory
        x = self.sublayer[0](x, lambda x: self.self_attn(x, x, x, tgt_mask))
        x = self.sublayer[1](x, lambda x: self.src_attn(x, m, m, src_mask))
        return self.sublayer[2](x, self.feed_forward)
```

Scaled Dot-Product Attention

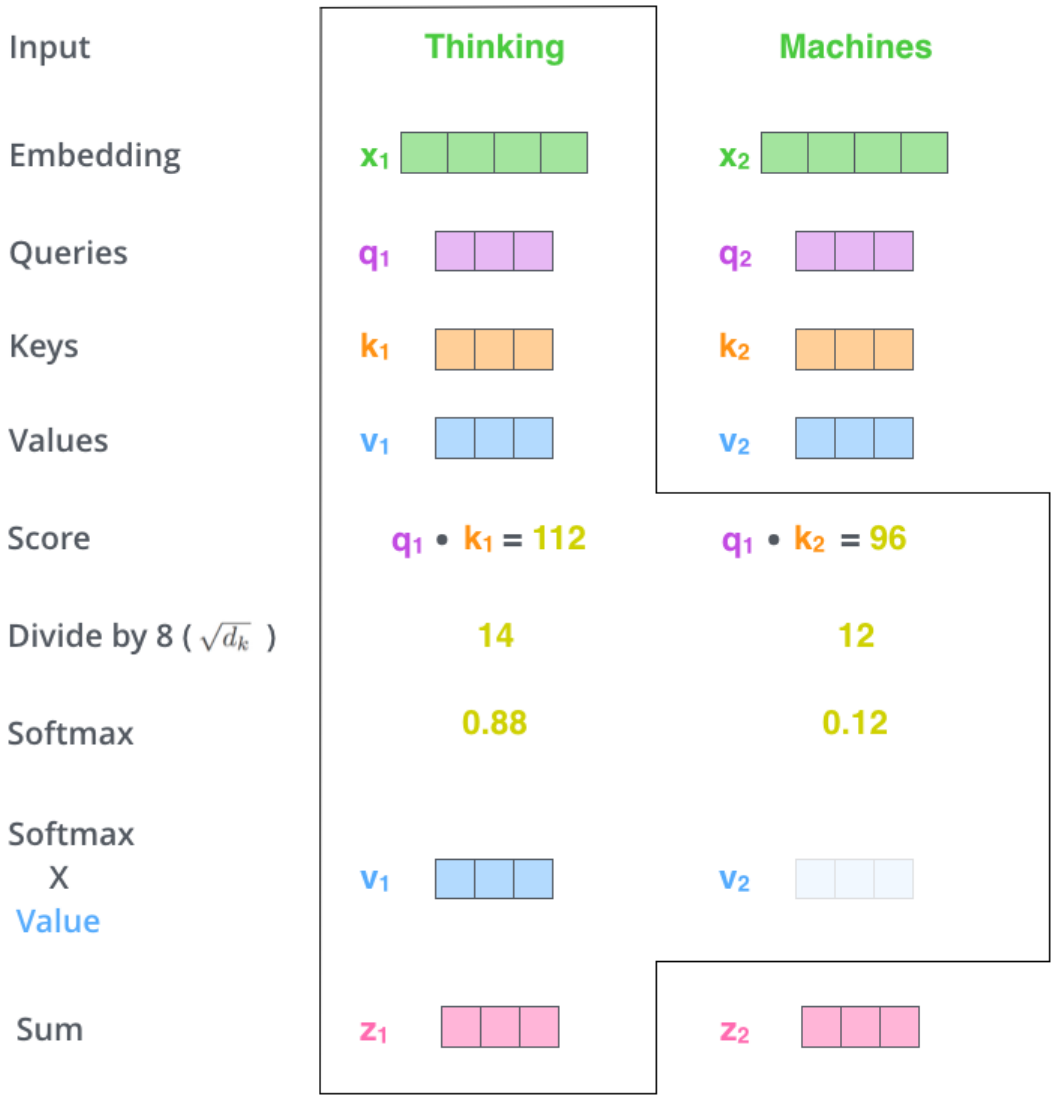
既然要`Attention`，那必然会有一个权重，这个权值的计算公式为

$$Attention(Q,K,V) = \text{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$

Q,K,V都是从词向量中经过线性变换得来的，如下图



计算过程就是得到Q,K,V后，Q和K做一个点积得到一个分数，再将这个分数开方（为了让梯度更稳定），然后`Softmax`得到一个分数，这个分数再乘以V得到加权后的值，最后求和得到`Output`



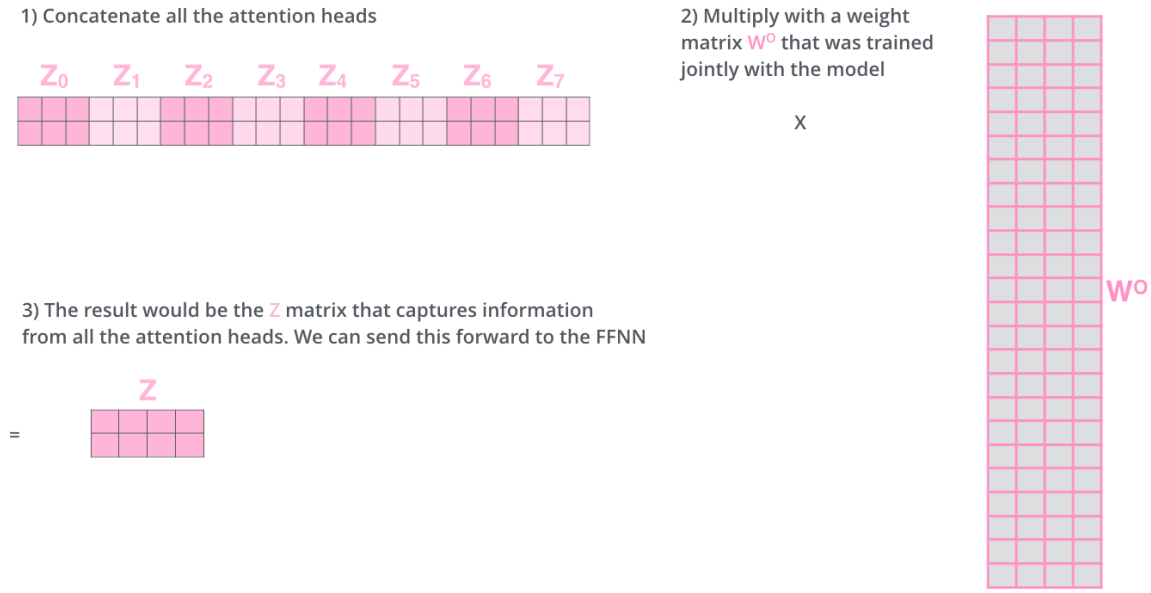
代码如下：

```
def attention(query, key, value, mask=None, dropout=None):
    "Compute 'Scaled Dot Product Attention'"
    d_k = query.size(-1)
    scores = torch.matmul(query, key.transpose(-2, -1)) \
             / math.sqrt(d_k)
    if mask is not None:
        scores = scores.masked_fill(mask == 0, -1e9)
    p_attn = F.softmax(scores, dim = -1)
    if dropout is not None:
        p_attn = dropout(p_attn)
    return torch.matmul(p_attn, value), p_attn
```

Multi-Head Attention

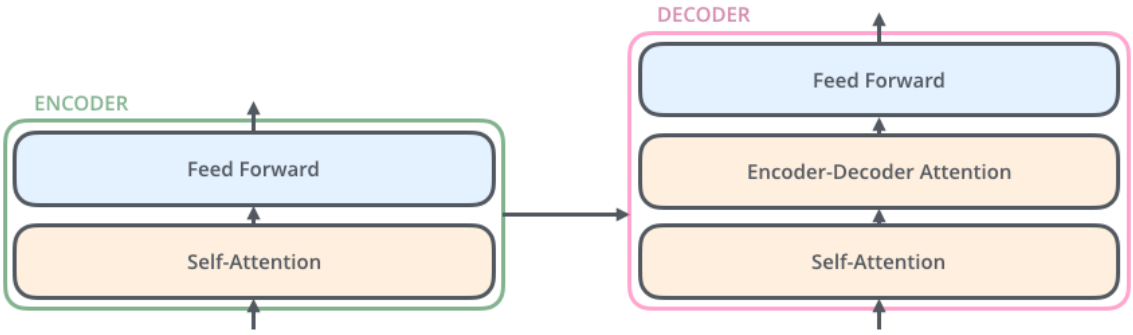
$$MultiHead(Q,K,V) = Concat(head_1,\dots,head_h)W^O$$
$$where\ head_i = Attention(QW_i^Q, KW_i^Q, VW_i^V)$$

简而言之就是把`Scaled Dot-Product Attention`做`h`次，把所有结果拼起来再做一次卷积压缩，如下图



公式里的W_i^Q起的是压缩维数的作用，比如h=8的话，维数就会被压缩为原来的八分之一，这样计算量和`single-head attention`就差不多了

`Multi-Head Attention`在网络中有三处，其中两个是`Encoder`和`Decoder`的`self-attention`，还有一个是`Encoder-Decoder Attention`，其中`Encoder`的`self-attention`作为`key`和`value`，`Decoder`的`self-attention`作为`query`



代码如下：

```
class MultiHeadedAttention(nn.Module):
    def __init__(self, h, d_model, dropout=0.1):
        "Take in model size and number of heads."
        super(MultiHeadedAttention, self).__init__()
        assert d_model % h == 0
        # We assume d_v always equals d_k
        self.d_k = d_model // h
        self.h = h
        self.linears = clones(nn.Linear(d_model, d_model), 4)
        self.attn = None
        self.dropout = nn.Dropout(p=dropout)

    def forward(self, query, key, value, mask=None):
        "Implements Figure 2"
        if mask is not None:
            # Same mask applied to all h heads.
            mask = mask.unsqueeze(1)
```

```
        nbatches = query.size(0)

        # 1) Do all the linear projections in batch from d_model => h x d_k
        query, key, value = \
            [l(x).view(nbatches, -1, self.h, self.d_k).transpose(1, 2)
             for l, x in zip(self.linears, (query, key, value))]

        # 2) Apply attention on all the projected vectors in batch.
        x, self.attn = attention(query, key, value, mask=mask,
                                 dropout=self.dropout)

        # 3) "Concat" using a view and apply a final linear.
        x = x.transpose(1, 2).contiguous() \
             .view(nbatches, -1, self.h * self.d_k)
        return self.linears[-1](x)
```

Position-wise Feed-Forward Networks

`Encoder` 和 `Decoder` 的 `Feed Forward` 是一个全连接层，包含两次线性变换和一次 `ReLu`，公式如下

$$FFN(x) = \max(0, xW_1 + b_1)W_2 + b_2$$

代码如下：

```
class PositionwiseFeedForward(nn.Module):
    "Implements FFN equation."
    def __init__(self, d_model, d_ff, dropout=0.1):
        super(PositionwiseFeedForward, self).__init__()
        self.w_1 = nn.Linear(d_model, d_ff)
        self.w_2 = nn.Linear(d_ff, d_model)
        self.dropout = nn.Dropout(dropout)

    def forward(self, x):
        return self.w_2(self.dropout(F.relu(self.w_1(x))))
```

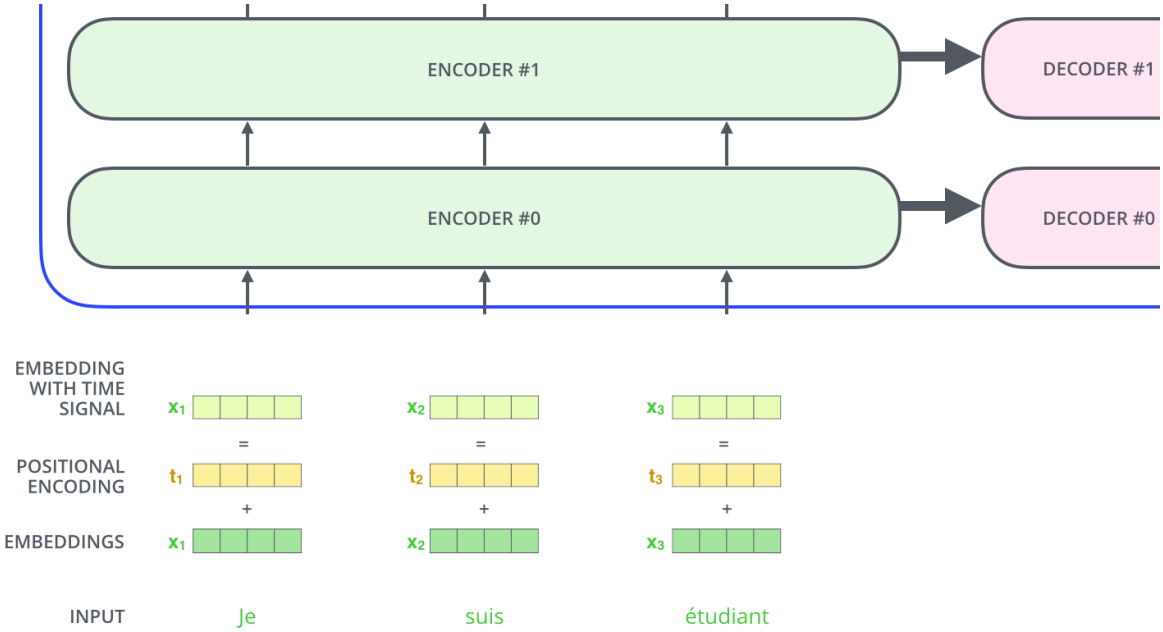
Embeddings and Softmax

词嵌入，唯一特别的是词嵌入的时候也会乘以$\sqrt{d_{model}}$

```
class Embeddings(nn.Module):
    def __init__(self, d_model, vocab):
        super(Embeddings, self).__init__()
        self.lut = nn.Embedding(vocab, d_model)
        self.d_model = d_model

    def forward(self, x):
        return self.lut(x) * math.sqrt(self.d_model)
```

Positional Encoding

这个东西是为了让模型可以了解到单词的顺序，方法就是在词嵌入的时候加上一个有规律的特征，让模型去学习，这个特征和单词的位置有关系，这样模型就应该可以学习到单词的位置信息



论文里写的公式是

$$PE_{(pos,2i)} = sin(pos/10000^{2i/d_{\text{model}}})$$
$$PE_{(pos,2i+1)} = cos(pos/10000^{2i/d_{\text{model}}})$$

这样做的目的是，让模型关注句子中词语的相对位置，而且这样也可以让模型遇到长句时更加稳定（直觉来看）

代码如下：

```
class PositionalEncoding(nn.Module):
    "Implement the PE function."
    def __init__(self, d_model, dropout, max_len=5000):
        super(PositionalEncoding, self).__init__()
        self.dropout = nn.Dropout(p=dropout)

        # Compute the positional encodings once in log space.
        pe = torch.zeros(max_len, d_model)
        position = torch.arange(0, max_len).unsqueeze(1)
        div_term = torch.exp(torch.arange(0, d_model, 2) *
                             -(math.log(10000.0) / d_model))
        pe[:, 0::2] = torch.sin(position * div_term)
        pe[:, 1::2] = torch.cos(position * div_term)
        pe = pe.unsqueeze(0)
        self.register_buffer('pe', pe)

    def forward(self, x):
        x = x + Variable(self.pe[:, :x.size(1)],
                         requires_grad=False)
        return self.dropout(x)
```

Full Model

```
def make_model(src_vocab, tgt_vocab, N=6,
               d_model=512, d_ff=2048, h=8, dropout=0.1):
    "Helper: Construct a model from hyperparameters."
    c = copy.deepcopy
    attn = MultiHeadedAttention(h, d_model)
```

```
    ff = PositionwiseFeedForward(d_model, d_ff, dropout)
    position = PositionalEncoding(d_model, dropout)
    model = EncoderDecoder(
        Encoder(EncoderLayer(d_model, c(attn), c(ff), dropout), N),
        Decoder(DecoderLayer(d_model, c(attn), c(attn),
                             c(ff), dropout), N),
        nn.Sequential(Embeddings(d_model, src_vocab), c(position)),
        nn.Sequential(Embeddings(d_model, tgt_vocab), c(position)),
        Generator(d_model, tgt_vocab))

    # This was important from their code.
    # Initialize parameters with Glorot / fan_avg.
    for p in model.parameters():
        if p.dim() > 1:
            nn.init.xavier_uniform(p)
    return model
```

advantages and disadvantages

优点：

- 由于没有用到RNN，可以很轻松的做到并行化

缺点：

- 缺失了位置信息，虽然加入位置编码一定程度上弥补了这一缺点，但在捕捉位置信息的能力上还是不如RNN

Soft Attention

个人觉得给的参考链接中`Attention`和`Soft Attention`应该是反了，所以这里介绍的是`Neural Machine Translation by Jointly Learning to Align and Translate`这篇论文

contribution

在传统的`Encoder-Decoder`模型中，输入会首先编码成C，然后再将C解码成输出，而固定长度的C会影响模型对于不同长度输入的表现，因此本文提出，利用一种注意力机制让网络根据输入输出对应的C，从而提升模型的表现

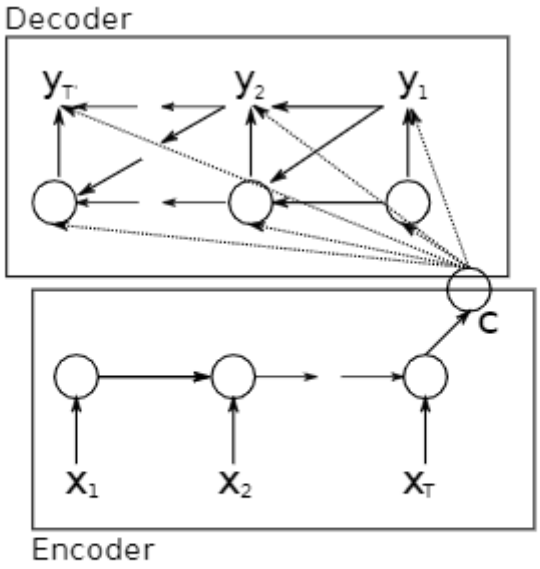


Figure 1: An illustration of the proposed RNN Encoder–Decoder.

method

在传统的`Encoder-Decoder`模型中，`Encoder`的作用相当于将输入编码到一个向量c，解码器的作用相当于根据输入和之前 的输出求当前步的输出，即求$p(y_i|y_1,\ldots,y_{i-1},x)$，由RNN的性质可知，这相当于$g(y_{i-1},s_i,c_i)$，其中$s_i$是RNN的`hidden state`，在传统模型中，对于输出的每一步，C是不会变，论文所做的改进就是针对C的生成，利用注意力机制使得输出的每一步对应不同的C

论文使用的网络结构如下

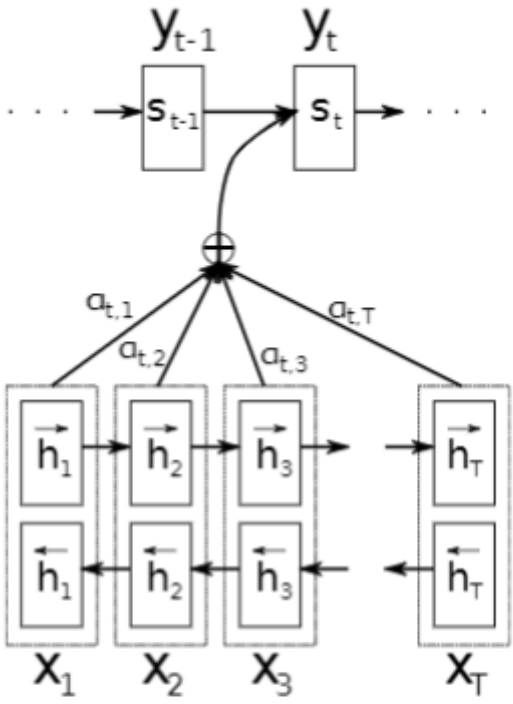


Figure 1: The graphical illustration of the proposed model trying to generate the t-th target word y_t given a source sentence $(x_1, x_2, \ldots, x_T)$.

c_i的生成由一个双向RNN和一个线性层处理得，对于每一个时间步，双向RNN有着正向和反向两个`hidden state`，将这两个`hidden state`拼接起来，再通过加权的方法，得到最终的上下文向量c_i，即$c_i = \sum_{j=1}^{T} a_{ij} h_j$，模型重点便在于注意力机制，即$a_{ij}$如何计算，论文引入了对齐模型，用于衡量原句的j位置和译句的i位置有多匹配，公式如下

$$a_{ij} = \frac{exp(e_{ij})}{\sum_{k=1}^{T} exp(e_{ik})}$$
$$e_{ij} = a(s_{i-1}, h_j)$$

也就是利用解码器`i-1`步的`hidden state`和编码器的`hidden state`计算得出匹配的程度

advantages and disadvantages

优点：

- 由于RNN网络理解长句的能力有限，在面对长句时，传统的`Encoder-Decoder`没办法很好的处理，而加入了`Attention`机制的模型在面对长句时也能很好的处理

缺点：

- `Attention`机制的加入意味着需要计算原句的每一个单词（字母），到译句的匹配程度，在原句长度很长时，`Attention`机制会导致计算的缓慢

Attention

contribution

提出了几种不同的Attention机制

method

与上一篇论文一样，这篇论文都是在改进c_i的生成方式，论文提出了两种`Attention`机制，`Global Attention`和`Local Attention`

Global Attention

和上一篇论文类似，结合所有`Encoder`层的`hidden state`来得出c_i

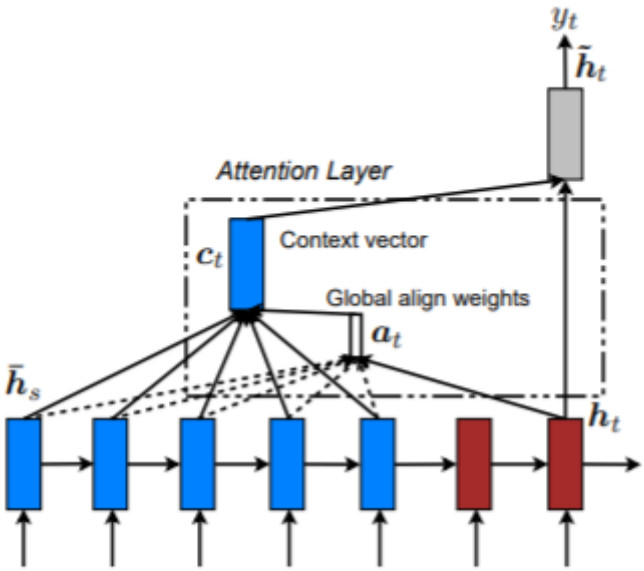


Figure 2: **Global attentional model** – at each time step t, the model infers a *variable-length* alignment weight vector $\boldsymbol{a}_t$ based on the current target state $\boldsymbol{h}_t$ and all source states $\bar{\boldsymbol{h}}_s$. A global context vector $\boldsymbol{c}_t$ is then computed as the weighted average, according to $\boldsymbol{a}_t$, over all the source states.

对于匹配程度的计算，论文给了四种方法

$$\text{score}(\boldsymbol{h}_t, \bar{\boldsymbol{h}}_s) = \begin{cases} \boldsymbol{h}_t^\top \bar{\boldsymbol{h}}_s & \textit{dot} \\ \boldsymbol{h}_t^\top \boldsymbol{W}_{\boldsymbol{a}} \bar{\boldsymbol{h}}_s & \textit{general} \\ \boldsymbol{v}_a^\top \tanh\left(\boldsymbol{W}_{\boldsymbol{a}}[\boldsymbol{h}_t; \bar{\boldsymbol{h}}_s]\right) & \textit{concat} \end{cases}$$

$$\boldsymbol{a}_t = \text{softmax}(\boldsymbol{W}_{\boldsymbol{a}} \boldsymbol{h}_t) \qquad \textit{location} \qquad (8)$$

测试结果表示`general`的效果比较好

Local Attention

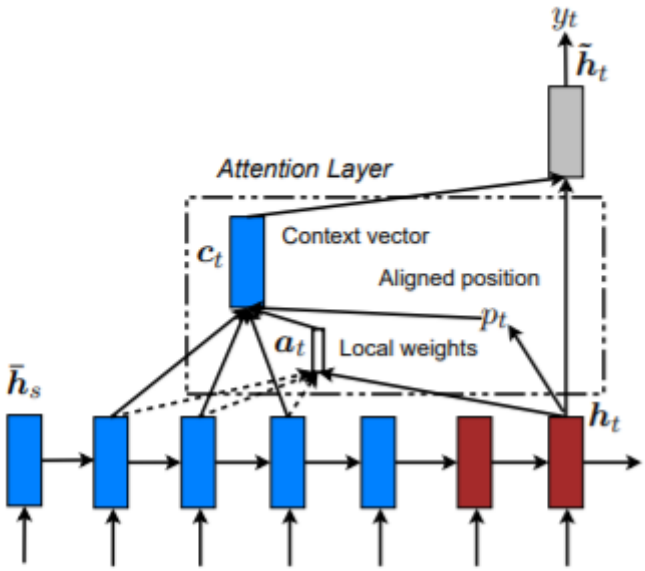


Figure 3: **Local attention model** – the model first predicts a single aligned position p_t for the current target word. A window centered around the source position p_t is then used to compute a context vector $\boldsymbol{c}_t$, a weighted average of the source hidden states in the window. The weights $\boldsymbol{a_t}$ are inferred from the current target state $\boldsymbol{h}_t$ and those source states $\bar{\boldsymbol{h}}_s$ in the window.

`Global Attention`的缺点在上一篇论文也有提到，就是对长句翻译，计算所有`hidden state`的匹配程度的计算量很大，而`Local Attention`只关注一部分的`hidden state`，相当于结合了`Hard Attention`和`Soft Attention`，对于`Decoder`中的时间步`t`，c_t只会根据以p_t为中心的窗口$[p_t - D, p_t + D]$计算，D是人工选定的，而p_t的计算则有两种方法

- **Monotonic alignment (local-m)**

直接让$p_t = t$

- **Predictive alignment (local-p)**

p_t的计算如下，其中W_p和v_p是可学习的参数，S是原句子的长度

$$p_t = S \cdot sigmoid(c_p^T tanh(W_p h_t))$$

权重的计算根据高斯分布加权，也就是说离p_t越远，权值越小，一般设$\sigma = \frac{D}{2}$

$$a_t(s) = align(h_t, \bar{h}_s) exp(-\frac{(s - p_t)^2}{2\sigma^2})$$

Input-feeding Approach

在传统的机器翻译中，一般会有一个`coverage set`用来记录有哪个词已经被翻译了，但在深度学习的模型中则没有这一信息，所以论文提出将$\tilde{h}$作为输入加入到下一次的计算中

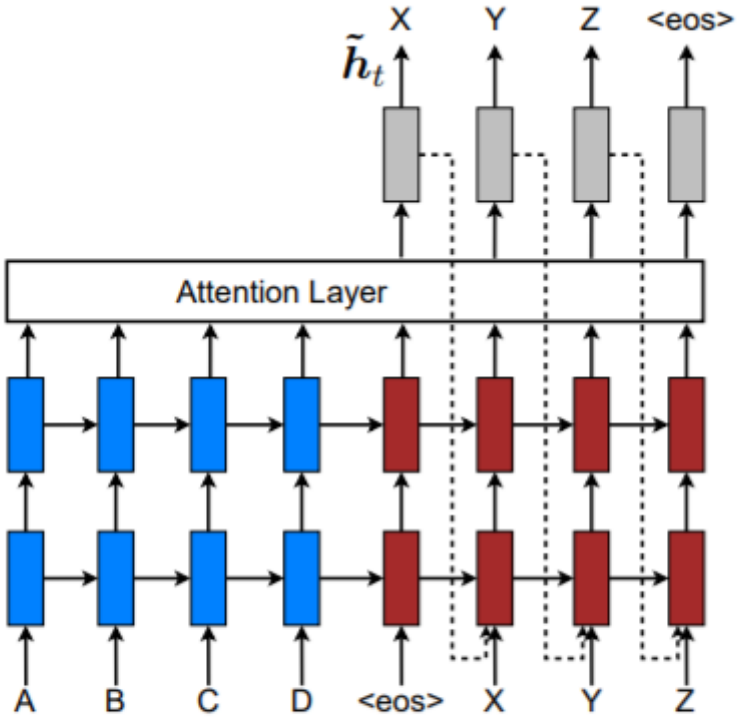


Figure 4: **Input-feeding approach** – Attentional vectors $\tilde{h}_t$ are fed as inputs to the next time steps to inform the model about past alignment decisions.

在其他的论文中，Bahdanau在生成上下文向量的时候加入上一次的上下文向量，可能也起到了类似的作用，然而没有分析说明这样会提高模型效果

Xu利用`doubly attentional`保证在字幕生成时，模型对于图像的每一部分都有相等的`Attention`

advantages and disadvantages

`Local Attention`的方法解决了`Global Attention`在长句翻译时计算量大的问题