中国科学院大学
University of Chinese Academy of Sciences

自然语言处理

第3讲 注意力机制

王 石 资康莉 刘 瑜

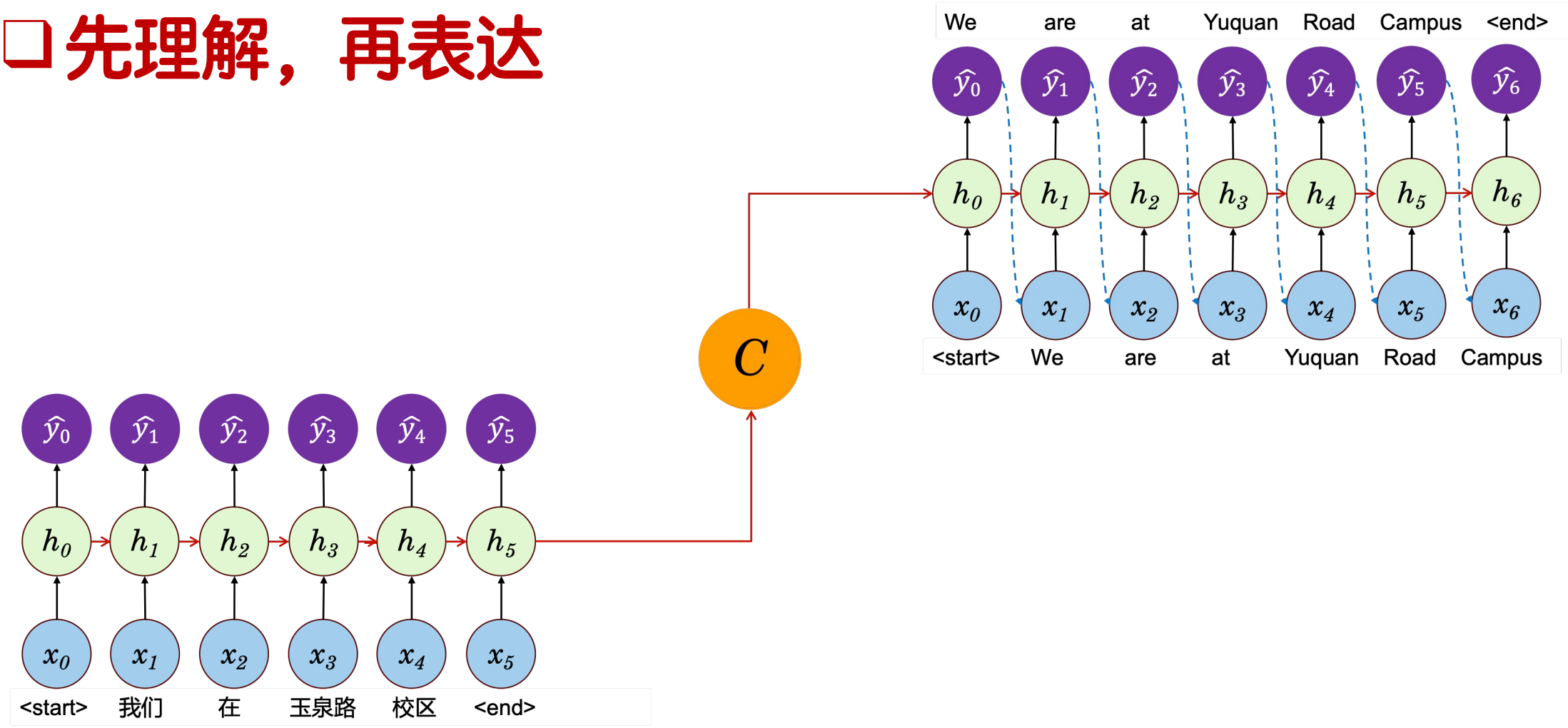
2026年春季课程

https://ictkc.github.io/teaching/

第三讲 注意力机制

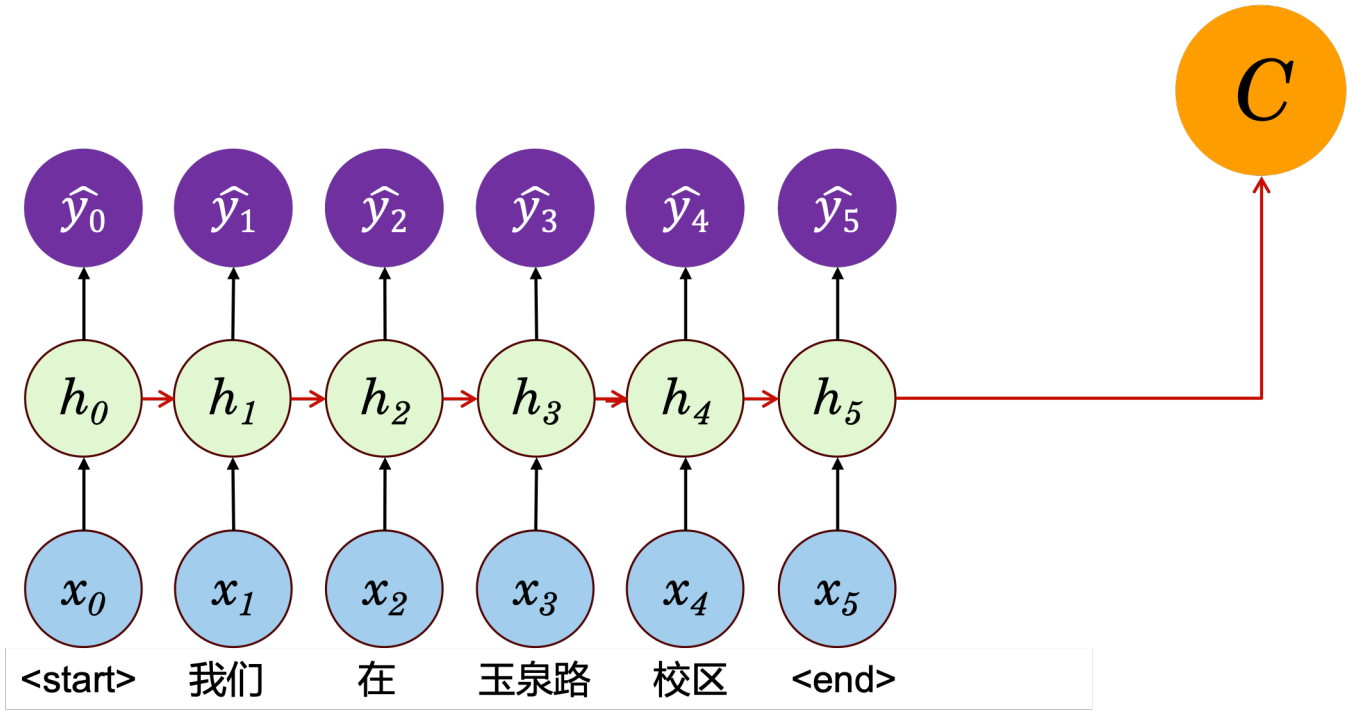
Encoder-Decoder原理

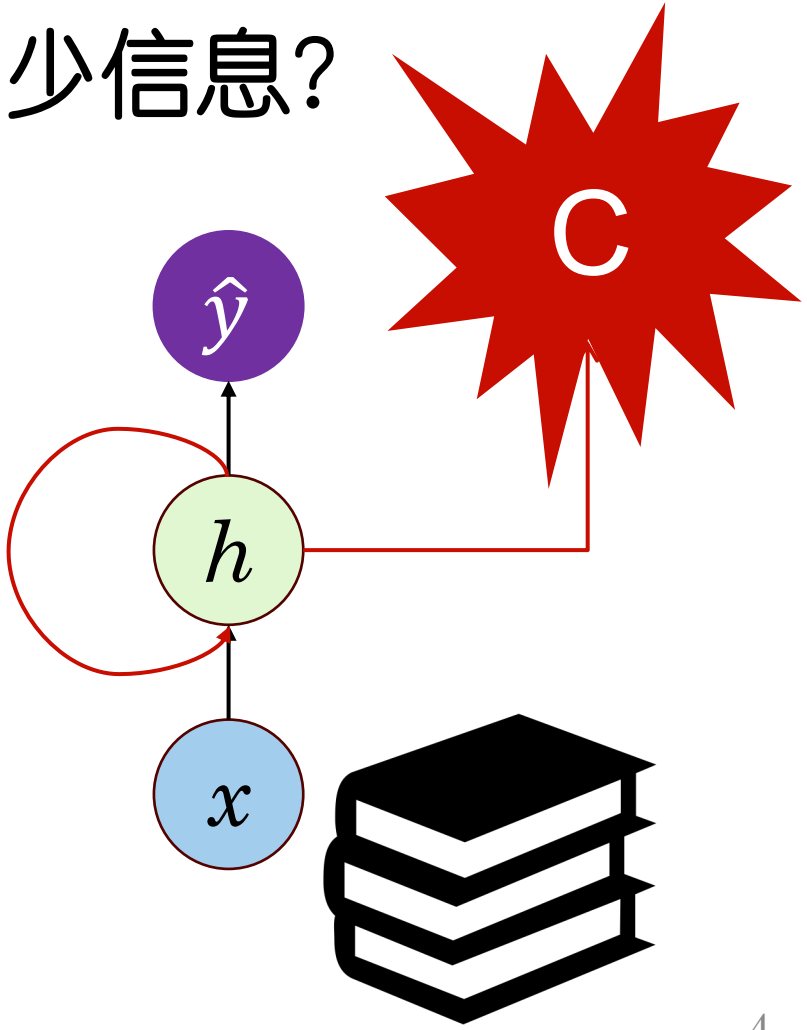
❑先理解，再表达



Encoder-Decoder缺点

- 区区一个固定长度的C，能容下多少信息？





C的作用：把输入所有信息压缩存储

the late Emperor was taken from us before he could finish his life's work, the restoration of the Han. Today, the empire is still divided in three, and our very survival is threatened. Yet still, the officials at court and the soldiers throughout the realm remain loyal to you, your majesty. Because they remember the late emperor, all of them, and they wish to repay his kindness in service to you. This is the moment to extend your divine influence, to honor the memory of the late Emperor and strengthen the morale of your officers. It is not the time to listen to bad advice or close your ears to the suggestions of loyal men. The emperors of the Western Han chose their courtiers wisely, and their dynasty flourished.

先帝创业未半而中道崩殂，今天下三分，益州疲弊，此诚危急存亡之秋也。然侍卫之臣不懈于内，忠志之士忘身于外者，盖追先帝之殊遇，欲报之于陛下也。诚宜开张圣听，以光先帝遗德，恢弘志士之气，不宜妄自菲薄，引喻失义，以塞忠谏之路也。

其他NLP任务还有更长的上下文

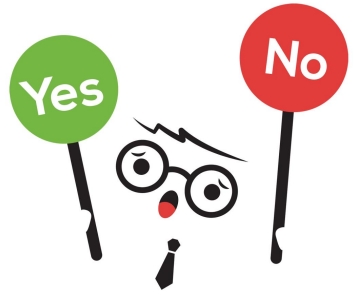
第七回 八卦炉中逃大圣 五行山下定心猿

……忽一日，开炉取丹。那大圣双手捂着眼，正自搓揉流涕，只听得炉头声响，猛睁睛看见光明，他就忍不住将身一纵，跳出丹炉，唿喇一声，**蹬倒八卦炉**，往外就走……

C

第六十回 牛魔王罢战赴华筵 孙行者二调芭蕉扇

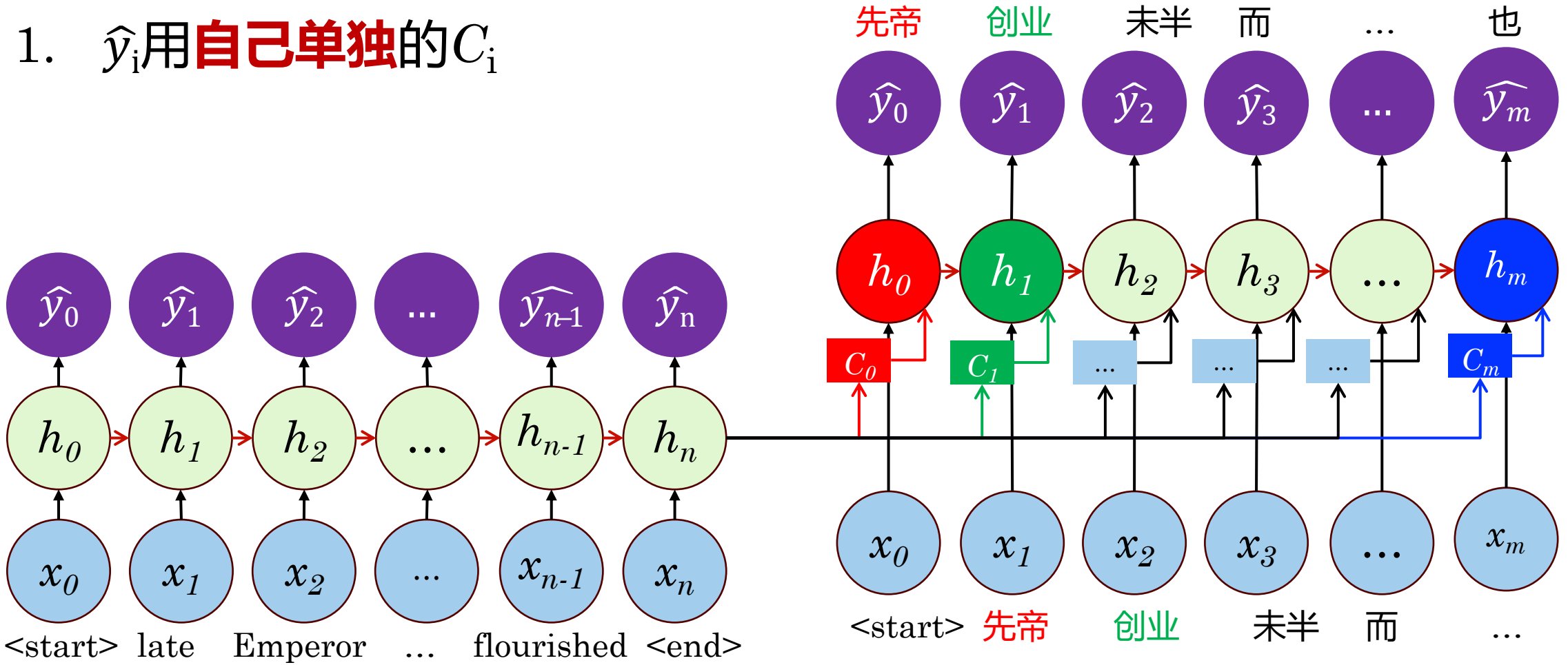
……土地道：“这火原是大圣放的。”行者怒道：“我在那里，你这等乱谈！**我可是放火之辈？**”



目 录

如果一个C解决不了，那就2个

1. $\hat{y}_i$用**自己单独**的C_i

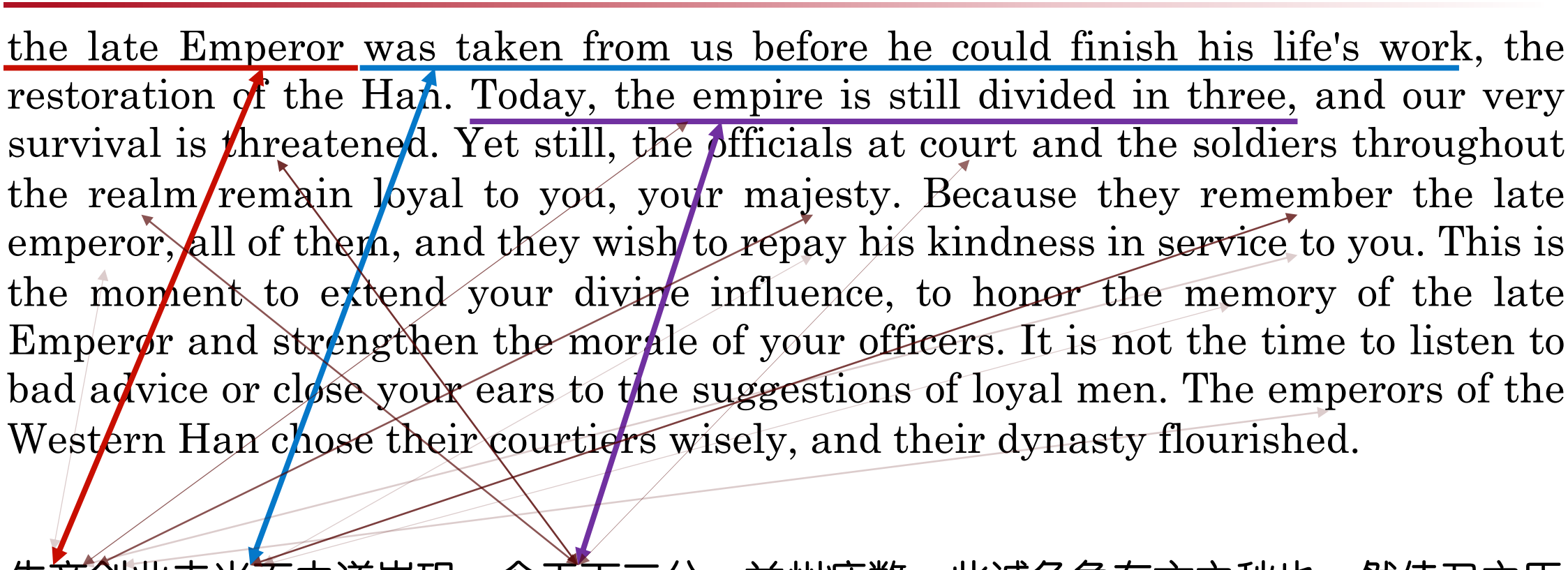


注意力机制：C_i需多注意和翻译它有关的词

the late Emperor was taken from us before he could finish his life's work, the restoration of the Han. Today, the empire is still divided in three, and our very survival is threatened. Yet still, the officials at court and the soldiers throughout the realm remain loyal to you, your majesty. Because they remember the late emperor, all of them, and they wish to repay his kindness in service to you. This is the moment to extend your divine influence, to honor the memory of the late Emperor and strengthen the morale of your officers. It is not the time to listen to bad advice or close your ears to the suggestions of loyal men. The emperors of the Western Han chose their courtiers wisely, and their dynasty flourished.

先帝创业未半而中道崩殂，今天下三分，益州疲弊，此诚危急存亡之秋也。然侍卫之臣不懈于内，忠志之士忘身于外者，盖追先帝之殊遇，欲报之于陛下也。诚宜开张圣听，以光先帝遗德，恢弘志士之气，不宜妄自菲薄，引喻失义，以塞忠谏之路也。

注意：不是“只注意”，是“多注意”

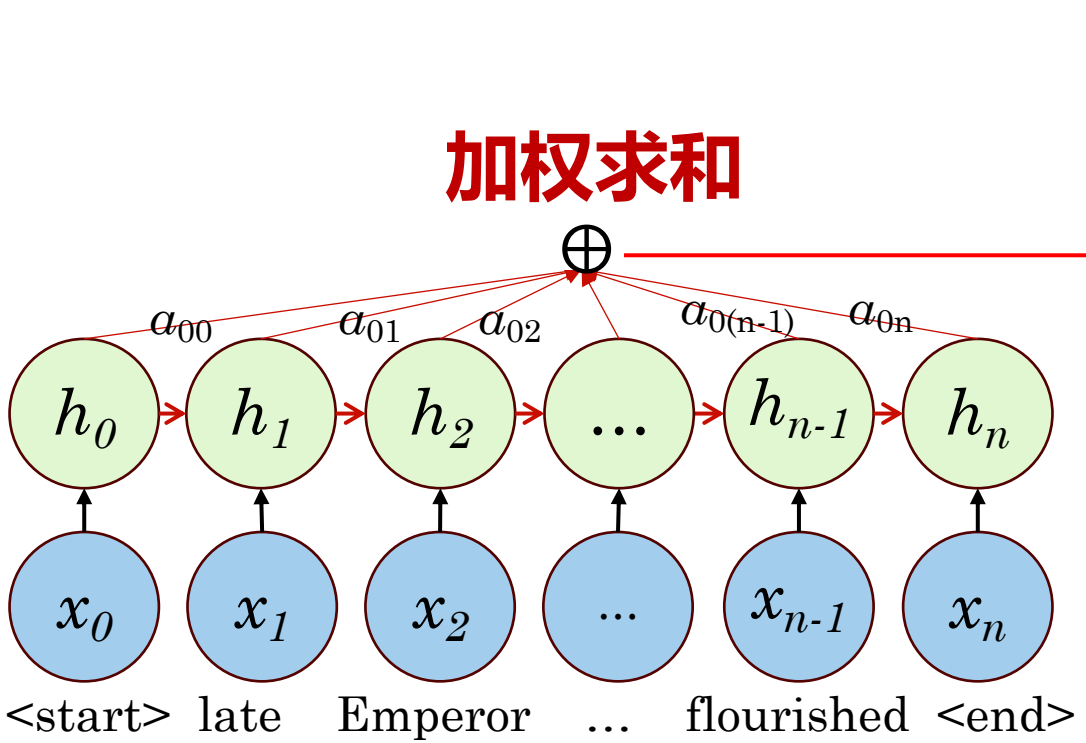


the late Emperor was taken from us before he could finish his life's work, the restoration of the Han. Today, the empire is still divided in three, and our very survival is threatened. Yet still, the officials at court and the soldiers throughout the realm remain loyal to you, your majesty. Because they remember the late emperor, all of them, and they wish to repay his kindness in service to you. This is the moment to extend your divine influence, to honor the memory of the late Emperor and strengthen the morale of your officers. It is not the time to listen to bad advice or close your ears to the suggestions of loyal men. The emperors of the Western Han chose their courtiers wisely, and their dynasty flourished.

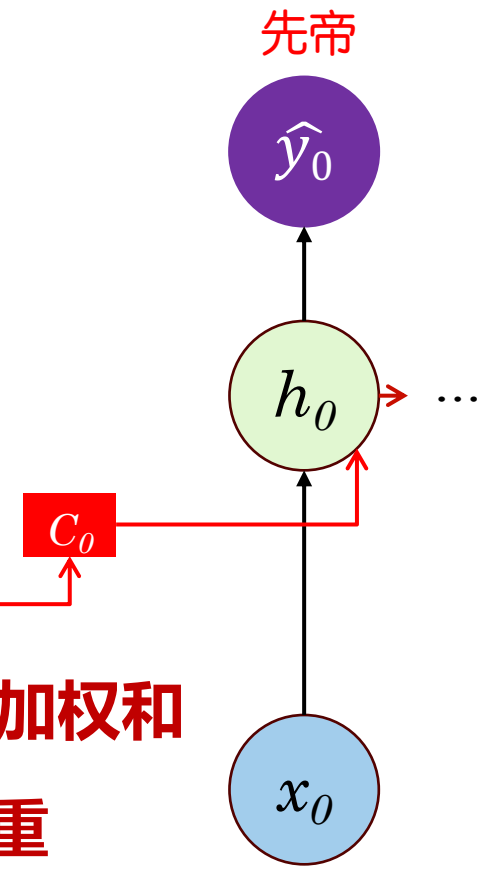
先帝创业未半而中道崩殂，今天下三分，益州疲弊，此诚危急存亡之秋也。然侍卫之臣不懈于内，忠志之士忘身于外者，盖追先帝之殊遇，欲报之于陛下也。诚宜开张圣听，以光先帝遗德，恢弘志士之气，不宜妄自菲薄，引喻失义，以塞忠谏之路也。

C_i如何计算

1. 来源于所有的源语言隐变量
2. 不同语言隐变量有不同的权重

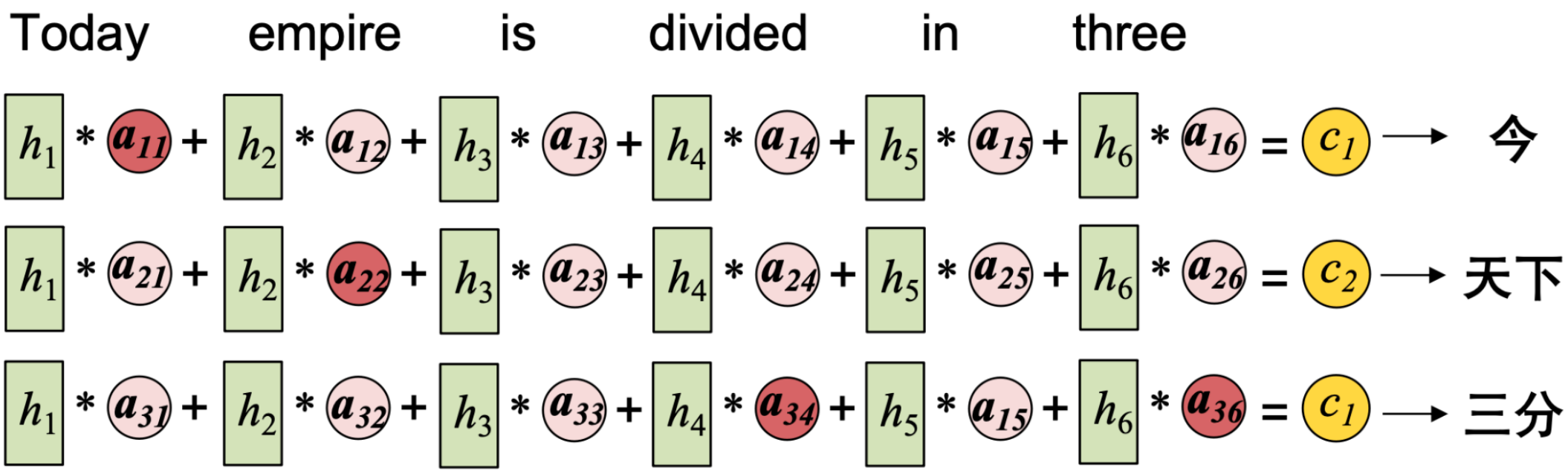


$$C_i = \sum_{j=0}^{n} a_{ij} h_j$$



- C_i是编码器中隐状态的**加权和**
- **a_{ij}是x_j对$\hat{y}_i$的重要性权重**

示例



问题：α_{ij}如何计算?

α_{ij}如何计算

α_{ij}特点分析

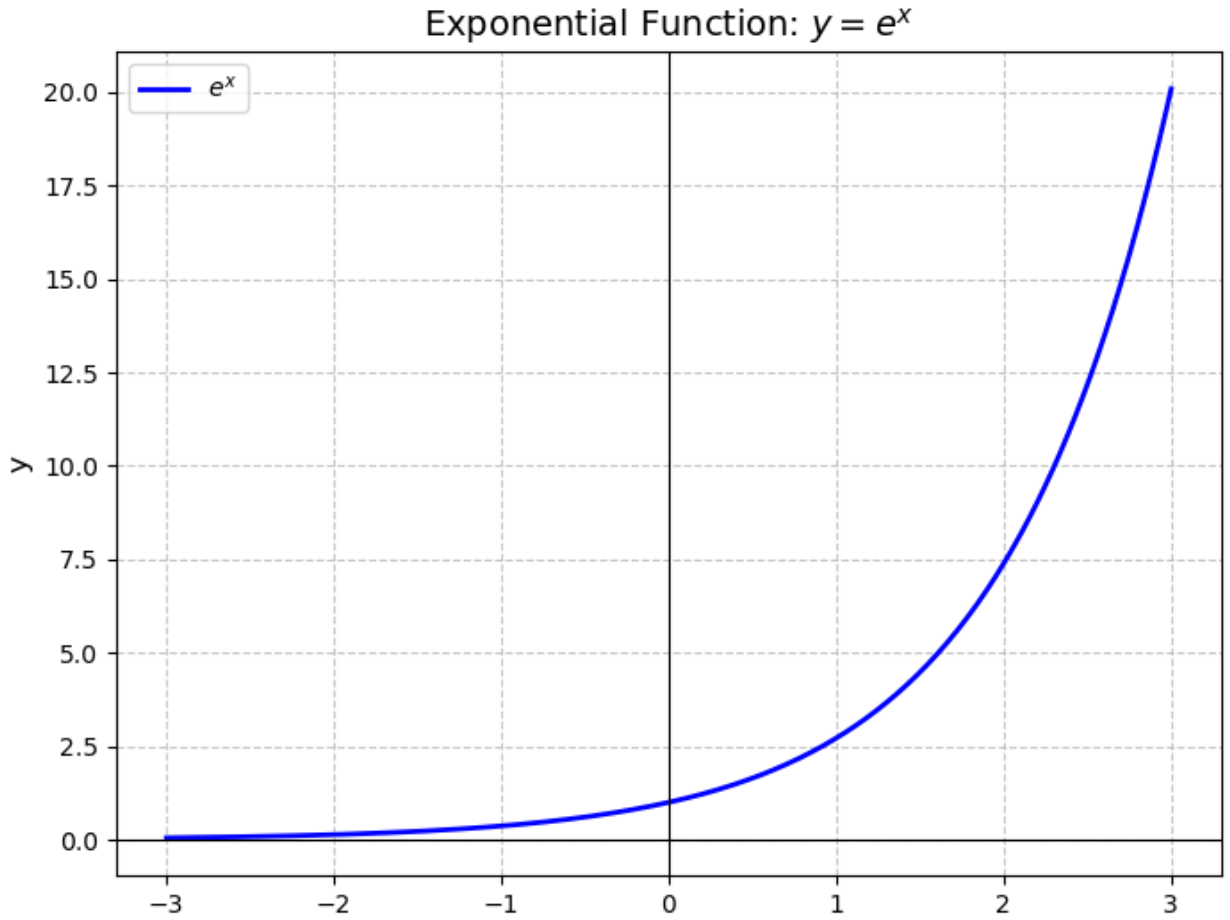
1. 归一（所有输入对$\hat{y}_i$的权重之和为1，$\sum_{j=0}^{n} a_{ij} = 1$）
2. 与编码器h_j、解码器h'_{i-1}有关
3. 属于模型参数，需训练产生

$$a_{ij} = \frac{e^{w_{ij}}}{\sum_{k=0}^{n} e^{w_{ik}}}$$ ← Softmax归一化

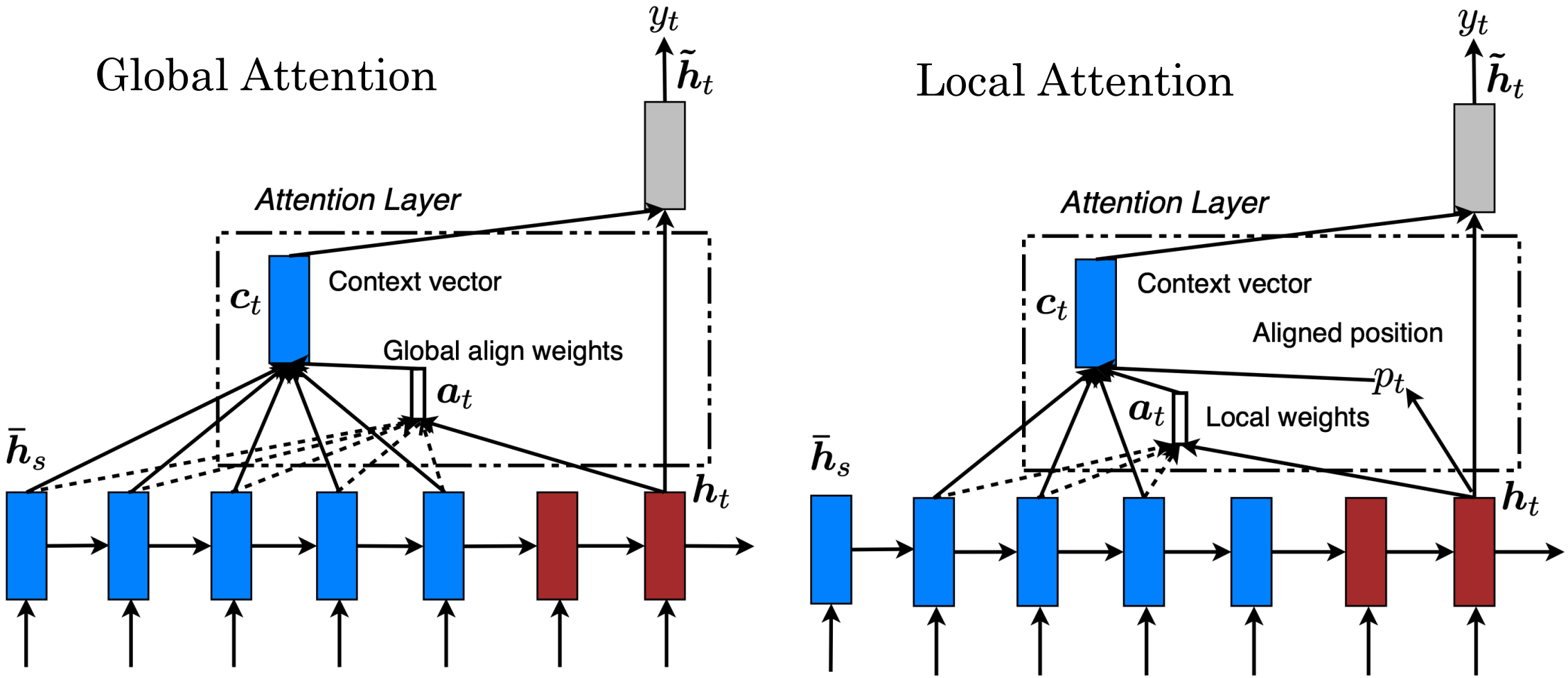
$$w_{ij} = \varphi\left(h'_{i-1}, h_j\right)$$ ← 权重对齐模型，需训练

补充：Softmax归一化为什么用e^x？

- 保证正值、放大差异、便于求导



Global Attention *v.s.* Local Attention



Luong, Minh-Thang, Hieu Pham,etc. "Effective approaches to attention-based neural machine translation." *EMNLP* 2015.

注意力机制开山之作

[PDF] Neural machine translation by jointly learning to align and translate

D Bahdanau, K Cho, Y Bengio

arXiv preprint arXiv:1409.0473, 2014 • peerj.com

Abstract

Neural machine translation is a recently proposed approach to machine translation. Unlike the traditional statistical machine translation, the neural machine translation aims at building a single neural network that can be jointly tuned to maximize the translation performance. The models proposed recently for neural machine translation often belong to a family of encoder–decoders and encode a source sentence into a fixed-length vector from which a decoder generates a translation. In this paper, we conjecture that the use of

展开

transformer 的前传

☆ 保存 引用 被引用次数：42458 相关文章 所有 28 个版本 »

Dzmitry Bahdanau, Kyunghyun Cho, and **Yoshua Bengio**. Neural machine translation by jointly learning to align and translate, 2014.

基于Attention+双向RNN的机器翻译

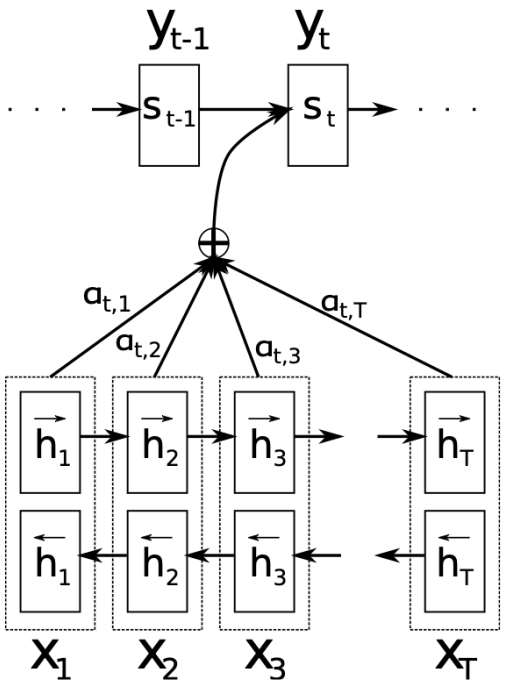
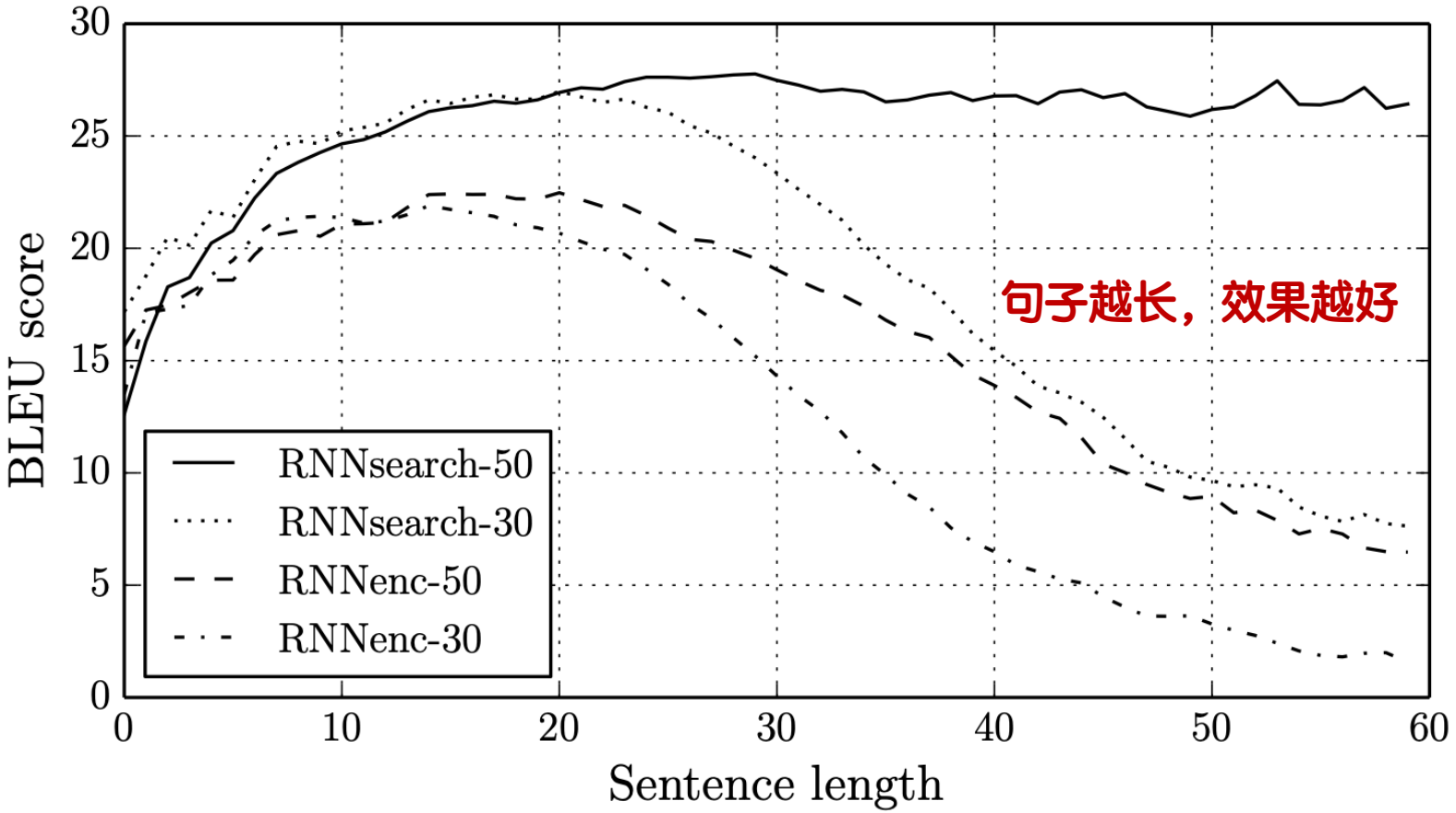
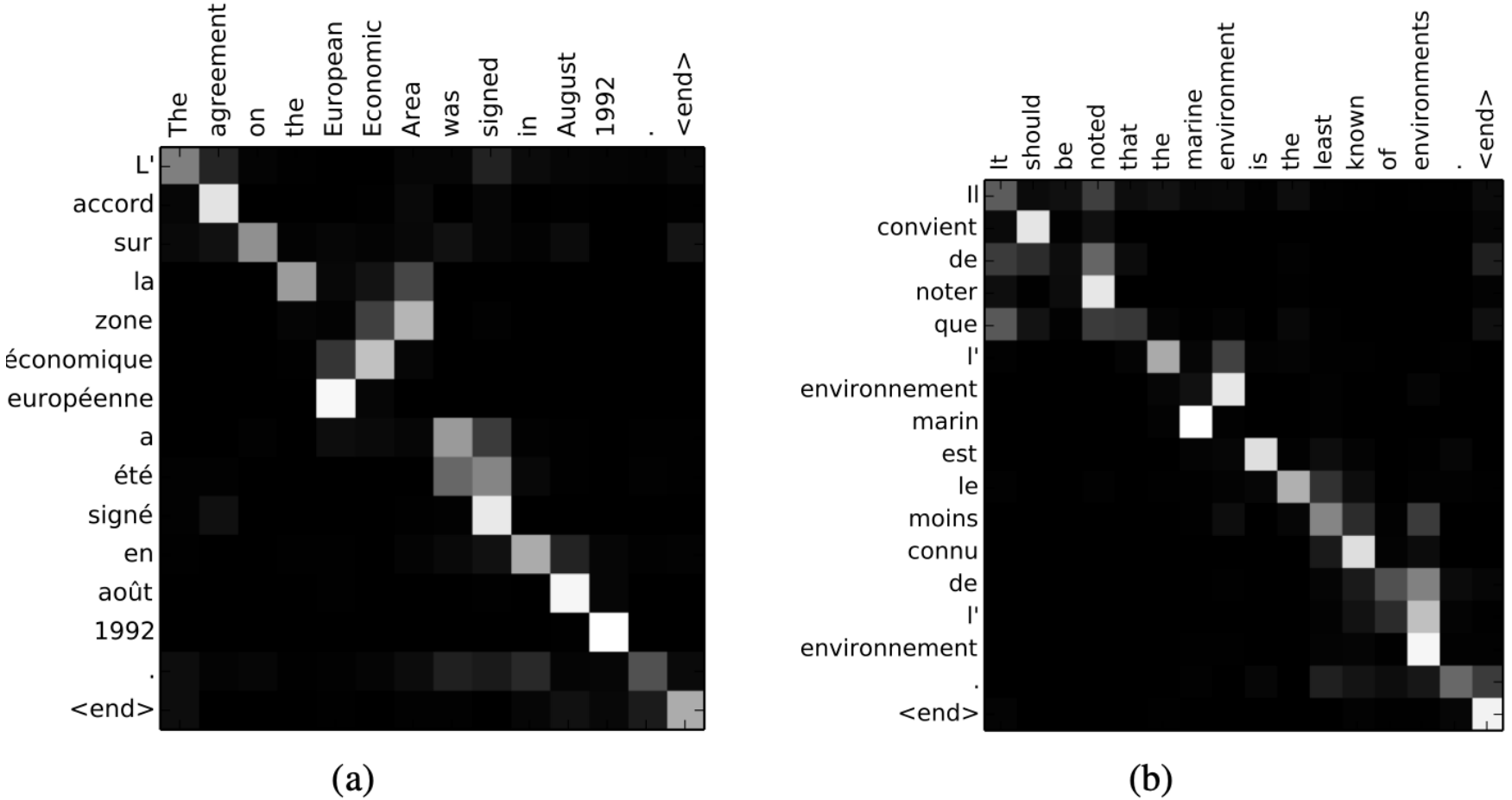


Figure 1: The graphical illustration of the proposed model trying to generate the t-th target word y_t given a source sentence $(x_1, x_2, \ldots, x_T)$.



基于Attention+双向RNN的机器翻译

展示注意力机制的双语对齐（英语-法语）效果，像素灰度对齐权重



再回到翻译的另一个问题：长距离依赖

the late Emperor was taken from us before he could finish his life's work, the restoration of the Han. Today, the empire is still divided in three, and our very survival is threatened. Yet still, the officials at court and the soldiers throughout the realm remain loyal to you, your majesty. Because they remember the late emperor, all of them, and they wish to repay his kindness in service to you. This is the moment to extend your divine influence, to honor the memory of the late Emperor and strengthen the morale of your officers. It is not the time to listen to bad advice or close your ears to the suggestions of loyal men. The emperors of the Western Han chose their courtiers wisely, and their dynasty flourished.

先帝创业未半而中道崩殂，今天下三分，益州疲弊，此诚危急存亡之秋也。然侍卫之臣不懈于内，忠志之士忘身于外者，盖追先帝之殊遇，欲报之于陛下也。诚宜开张圣听，以光先帝遗德，恢弘志士之气，不宜妄自菲薄，引喻失义，以塞忠谏之路也。

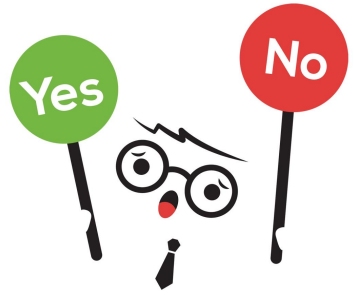
再看其他更长上下文的任务

第七回 八卦炉中逃大圣 五行山下定心猿

……忽一日，开炉取丹。那大圣双手捂着眼，正自搓揉流涕，只听得炉头声响，猛睁睛看见光明，他就忍不住将身一纵，跳出丹炉，唿喇一声，**蹬倒八卦炉**，往外就走……

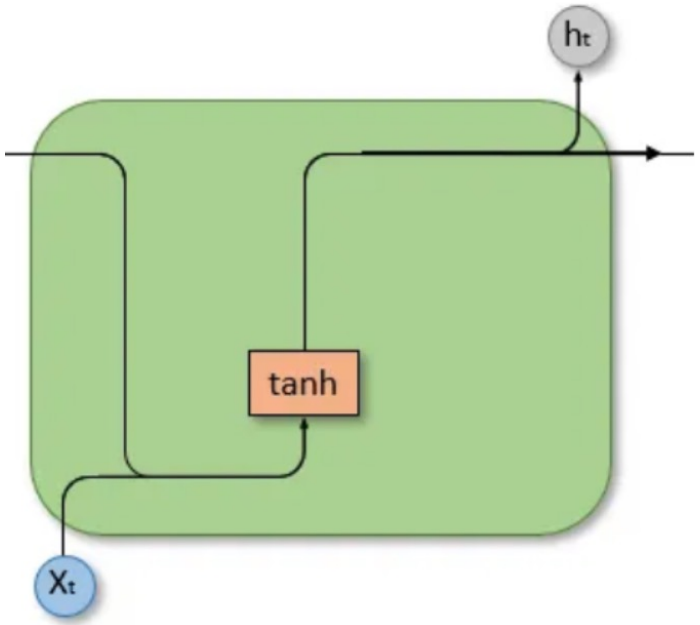
第六十回 牛魔王罢战赴华筵 孙行者二调芭蕉扇

……土地道：“这火原是大圣放的。”行者怒道：“我在那里，你这等乱谈！**我可是放火之辈？**”

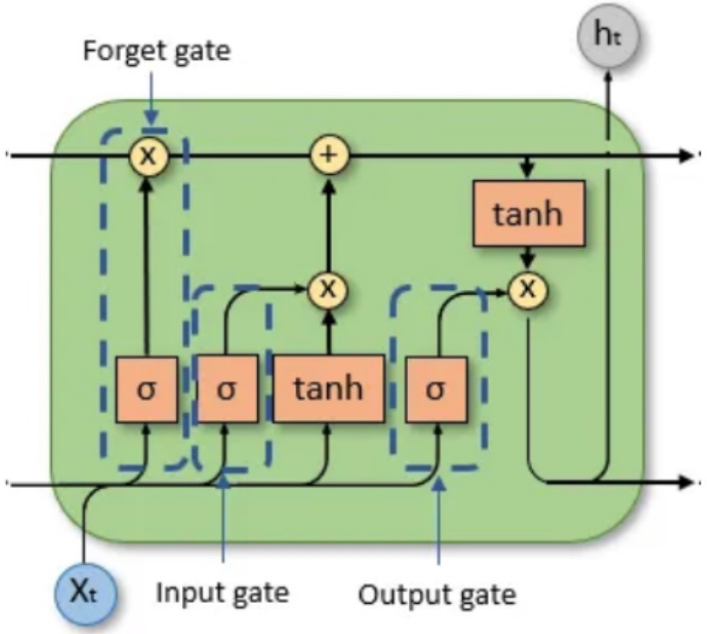


解决办法回顾

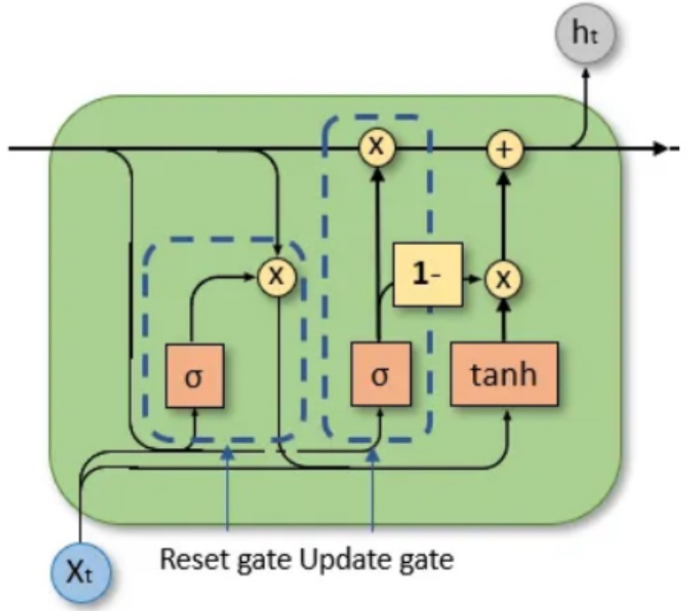
RNN



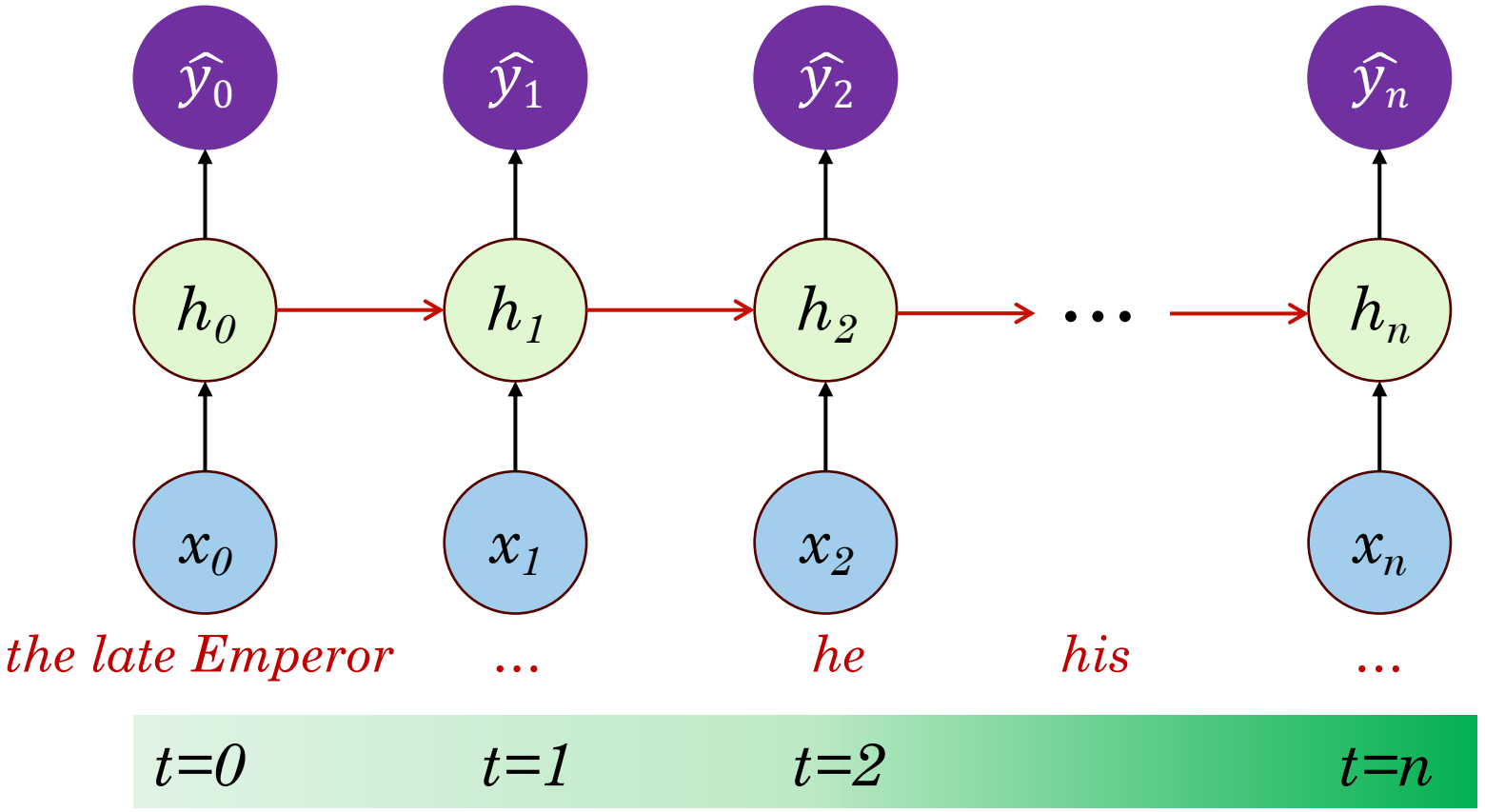
LSTM



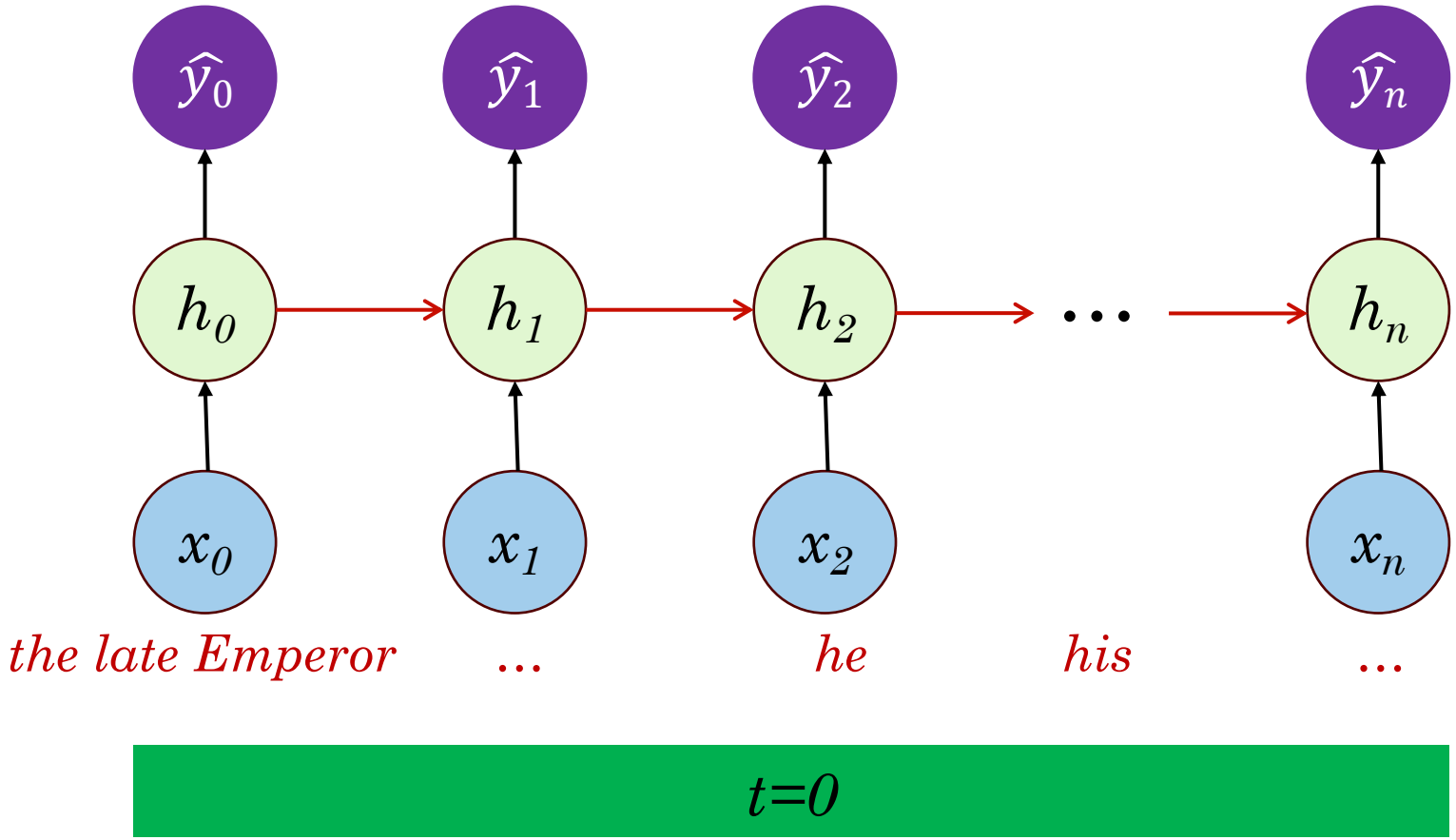
GRU



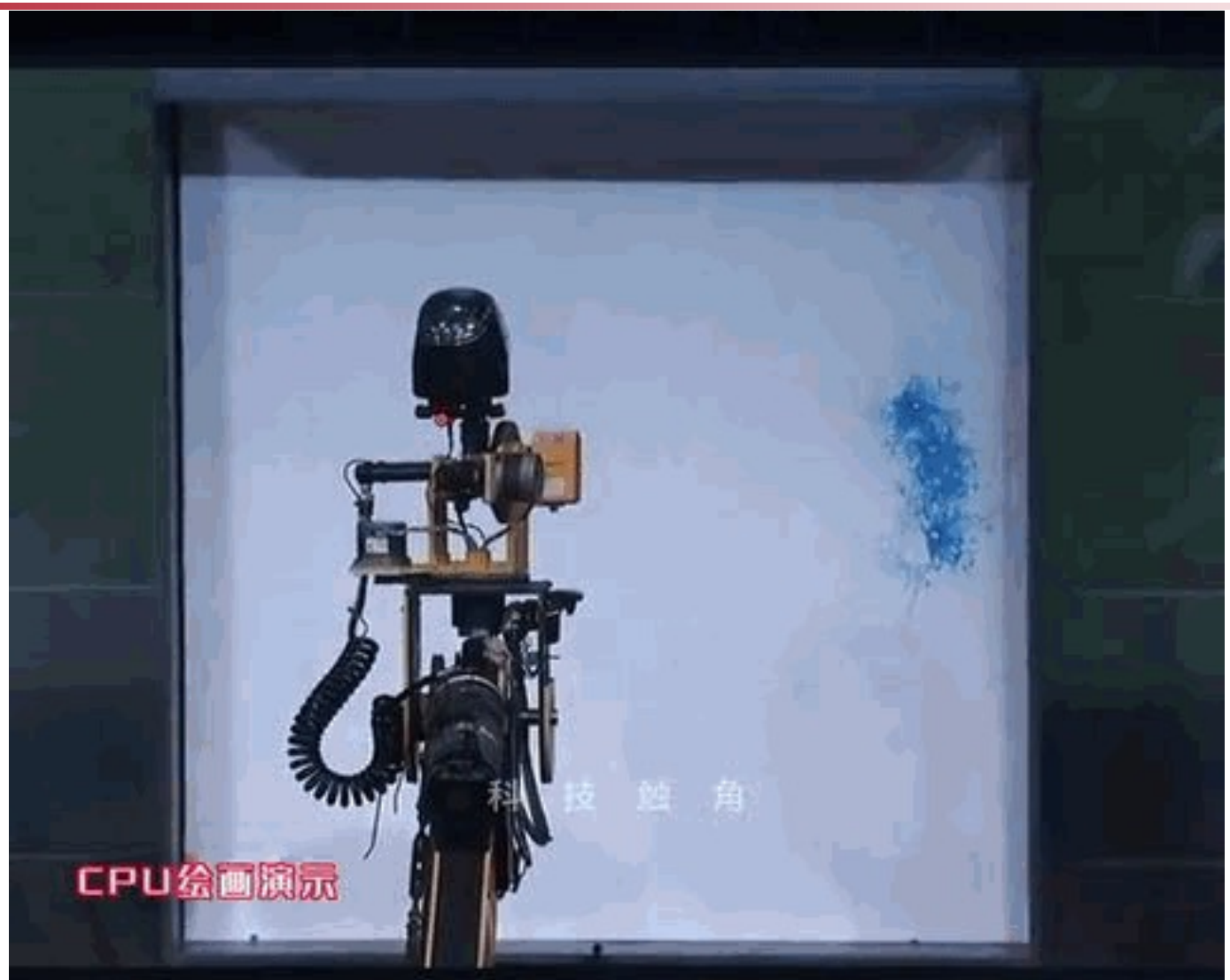
共同存在的问题：串性化，效率低



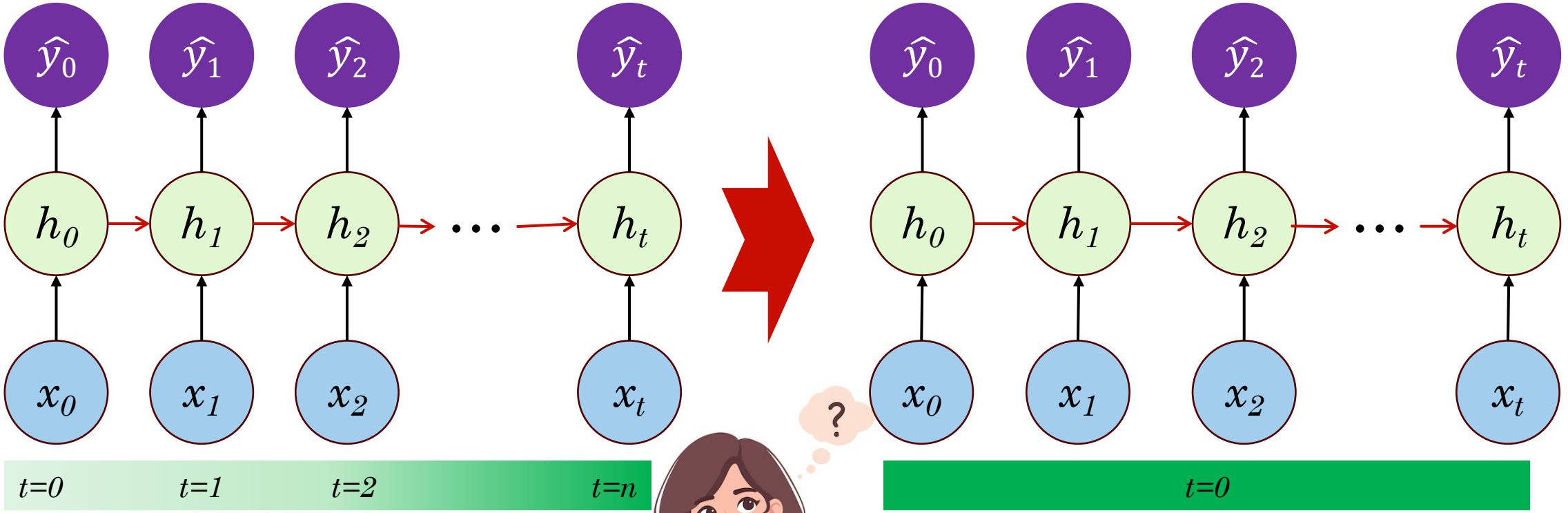
期望的并行化处理


$\hat{y}_0$
$\hat{y}_1$
$\hat{y}_2$
$\hat{y}_n$
h_0
h_1
h_2
$\cdots$
h_n
x_0
x_1
x_2
x_n
the late Emperor
…
he
his
…
t=0

串行 *v.s.* 并行

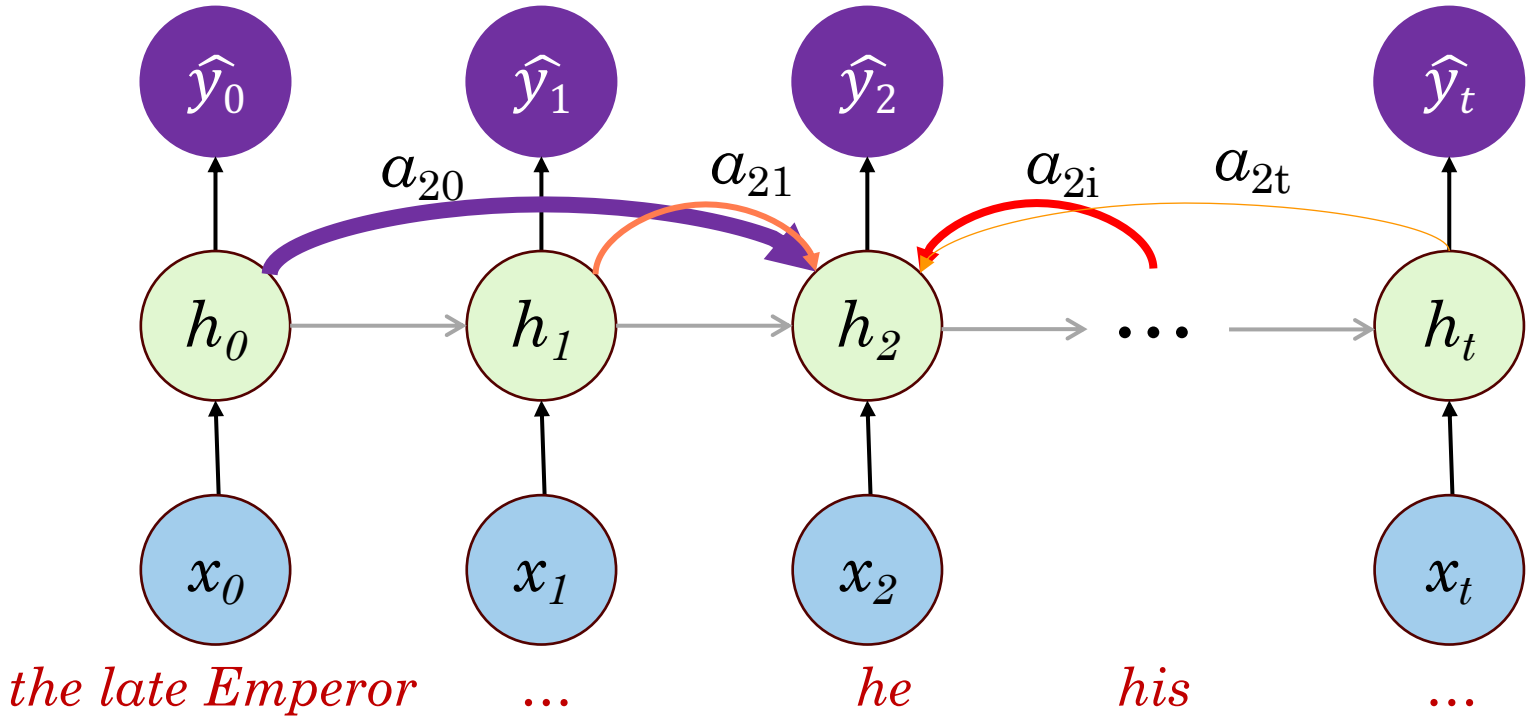


串行 *v.s.* 并行


$\hat{y}_0$ $\hat{y}_1$ $\hat{y}_2$ $\hat{y}_t$
h_0 h_1 h_2 … h_t
x_0 x_1 x_2 x_t
t=0 t=1 t=2 t=n
$\hat{y}_0$ $\hat{y}_1$ $\hat{y}_2$ $\hat{y}_t$
h_0 h_1 h_2 … h_t
x_0 x_1 x_2 x_t
t=0


?

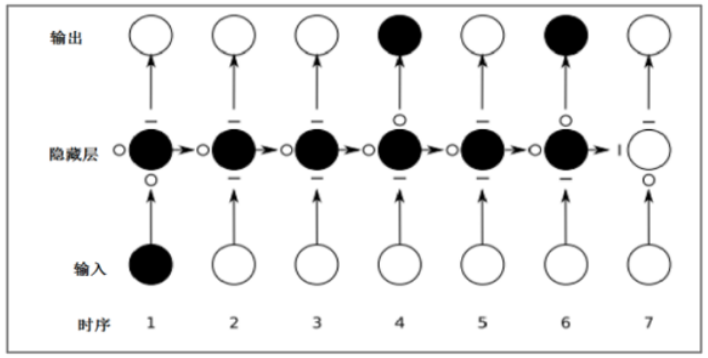
用注意力视角看上下文


$\hat{y}_0$
$\hat{y}_1$
$\hat{y}_2$
$\hat{y}_t$
a_{20}
a_{21}
a_{2i}
a_{2t}
h_0
h_1
h_2
...
h_t
x_0
x_1
x_2
x_t
the late Emperor
...
he
his
...

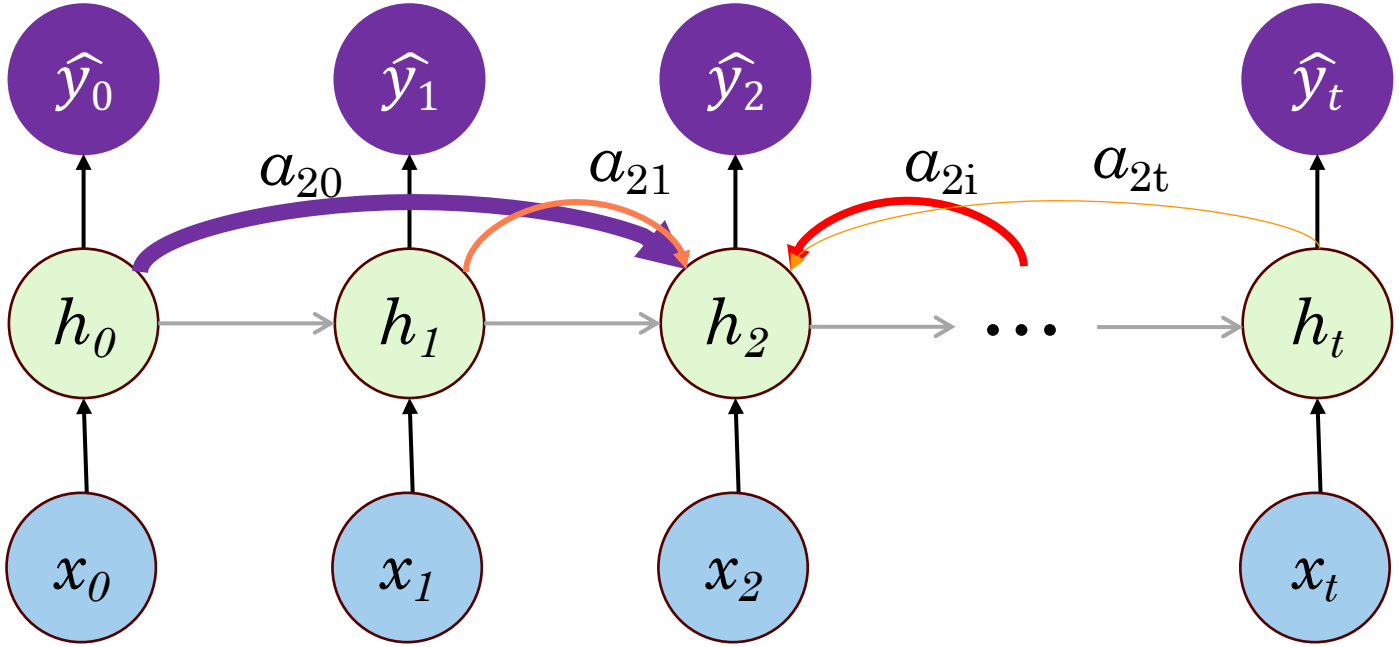
目 录

消除代代相传记忆的一个方法：查读

- 如果每个词都**知道“我该注意谁”**，那么就不再需要RNN中不断代代相传历史记忆，而是需要时去使用该注意的词的信息即可



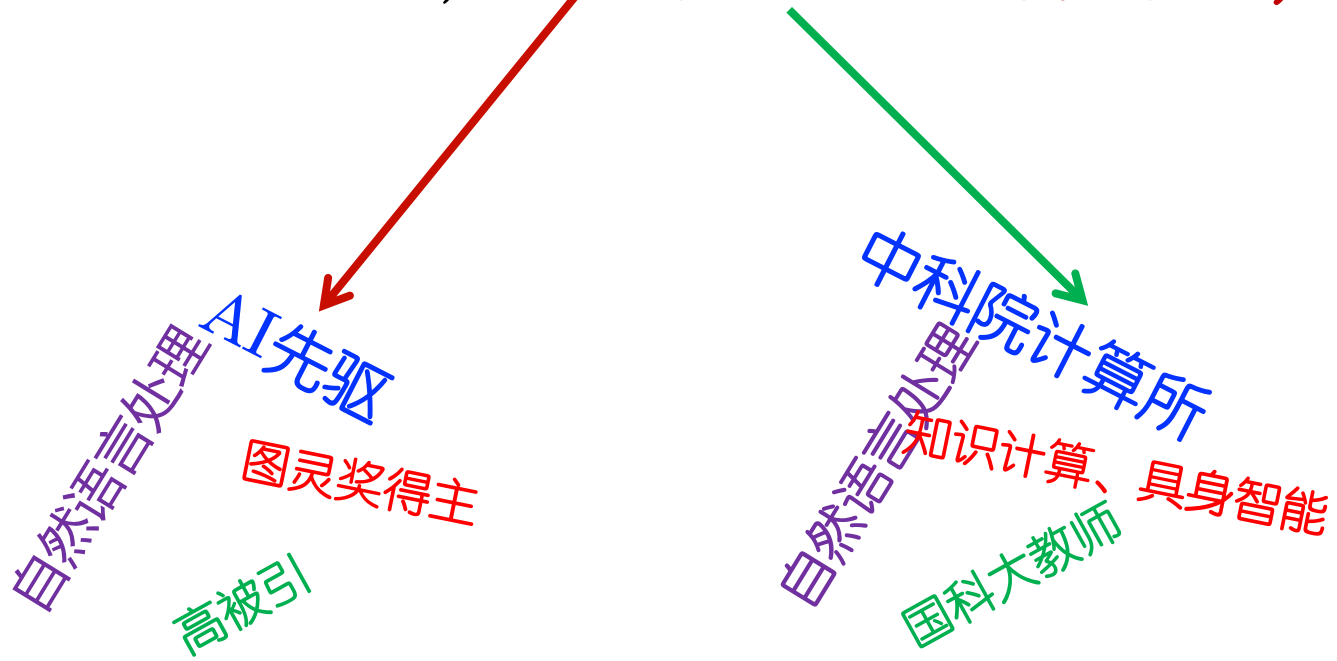
LSTM



怎么让每个词都知道“我该注意谁”？

若要每个人都知道“我该注意谁”，那么所有人都要回答

- 我要注意什么？ （我**该注意哪些方面，我要用来去找人**）
- 别人要想注意我，该怎么找到我？ （**我的标签，好让别人也能要回答**）



在NLP中，每个词也要回答

- 我要注意什么？ **(Query)**
- 别人要想注意我，该怎么找到我？ **(Key)**

那时候，柔嘉在家里等鸿渐回家来吃晚饭，希望他会跟妯母和好，到她厂里做事

W	*Q*	*K*	能获得的信息：*V*
柔嘉	我要被谁指代？	我是一个女性名字 我是主语	孙柔嘉，女，方鸿渐妻子；长圆脸，微有雀斑，两眼分得太开，使我常带着惊异的表情……
她	我指代谁？	我是一个女性代词	我就是个代词，用来指代女性……

在NLP中，每个词也要回答

- 我要注意什么？ **(Query)**
- 别人要想注意我，该怎么找到我？ **(Key)**
- 我的信息 **(Value)**

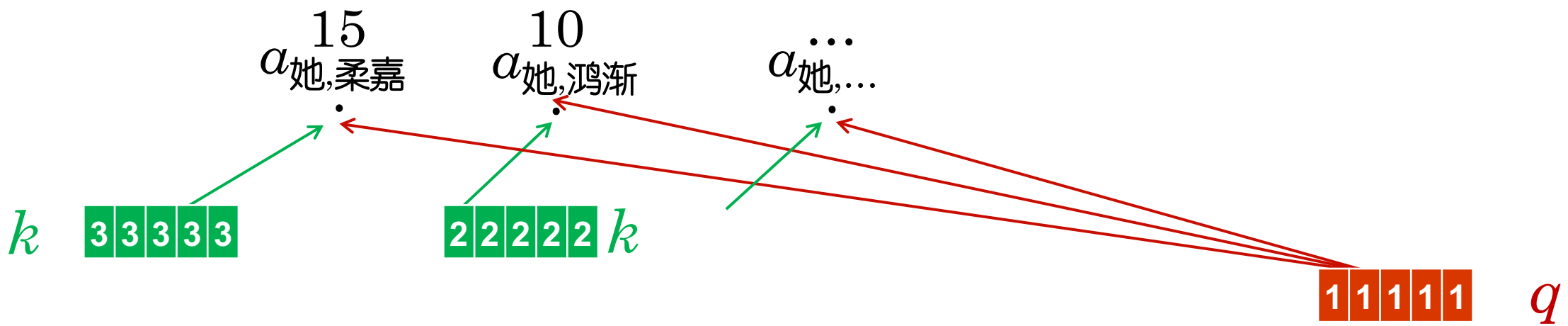
那时候，柔嘉在家里等鸿渐回家来吃晚饭，希望他会跟妣母和好，到她厂里做事

均为1*N向量（N为超参数）

W	*Q*	*K*	*V*
w_i	$q^i=$	$k^i=$	$v^i=$
w_j	$q^j=$	$k^j=$	$v^j=$

寻找该注意的词

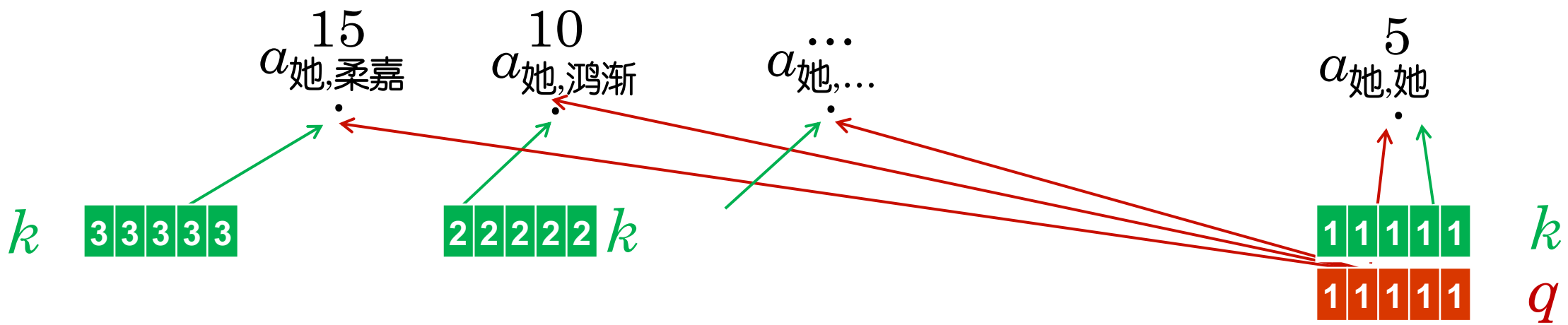
1. w_i对w_j的**注意力**： $\alpha_{i,j} = q^i \cdot k^j$



那时候， 柔嘉在家里等鸿渐回家来吃晚饭， 希望他会跟北母和好， 到她厂里做事

寻找该注意的词

2. 自己也不放过： $\alpha_{i,i} = q^i \cdot k^i$

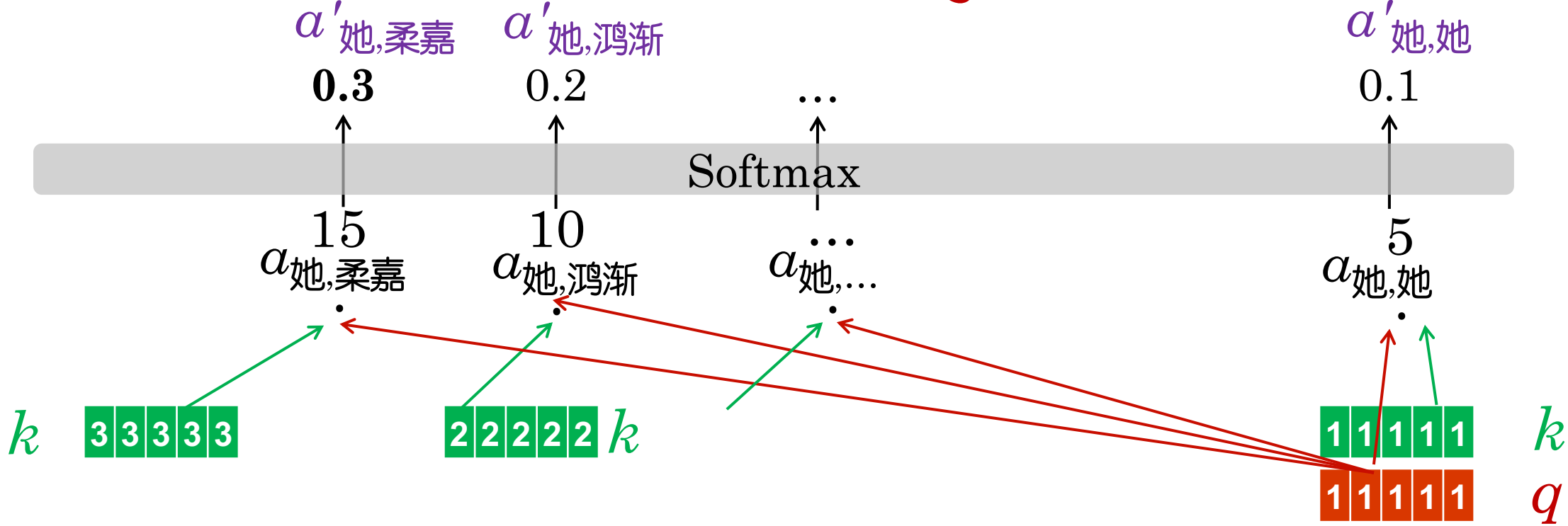


那时候， 柔嘉在家里等鸿渐回家来吃晚饭， 希望他会跟北母和好， 到她厂里做事

寻找该注意的词

OVER

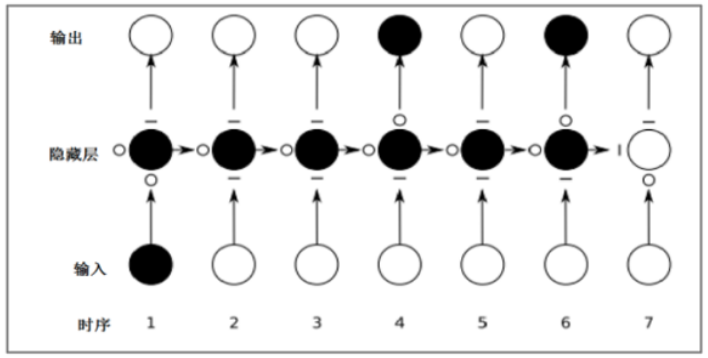
3. 归一化



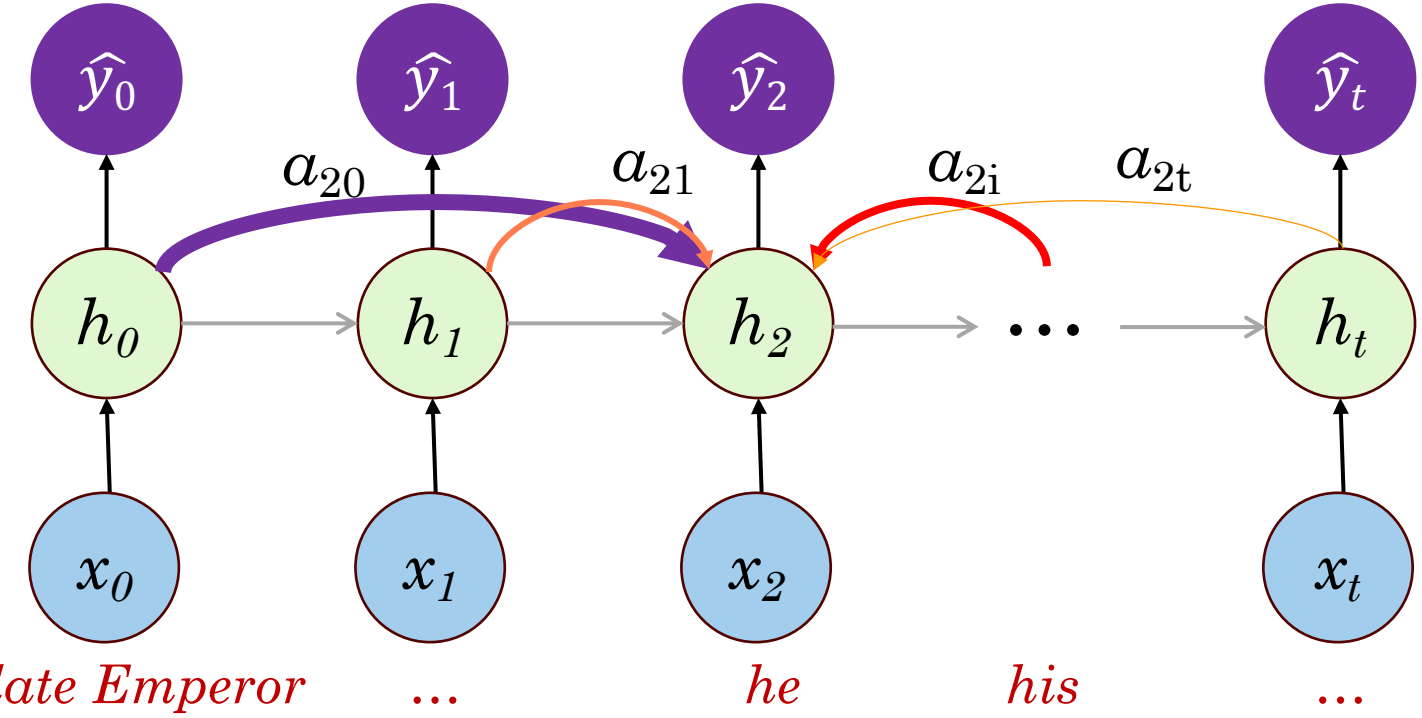
那时候， 柔嘉在家里等鸿渐回家来吃晚饭， 希望他会跟北母和好， 到她厂里做事

消除代代相传记忆的一个方法：查**读**

- 如果每个词都**知道“我该注意谁”**，那么就不再需要RNN中不断代代相传历史记忆，而是**需要时去使用该注意的词的信息**即可

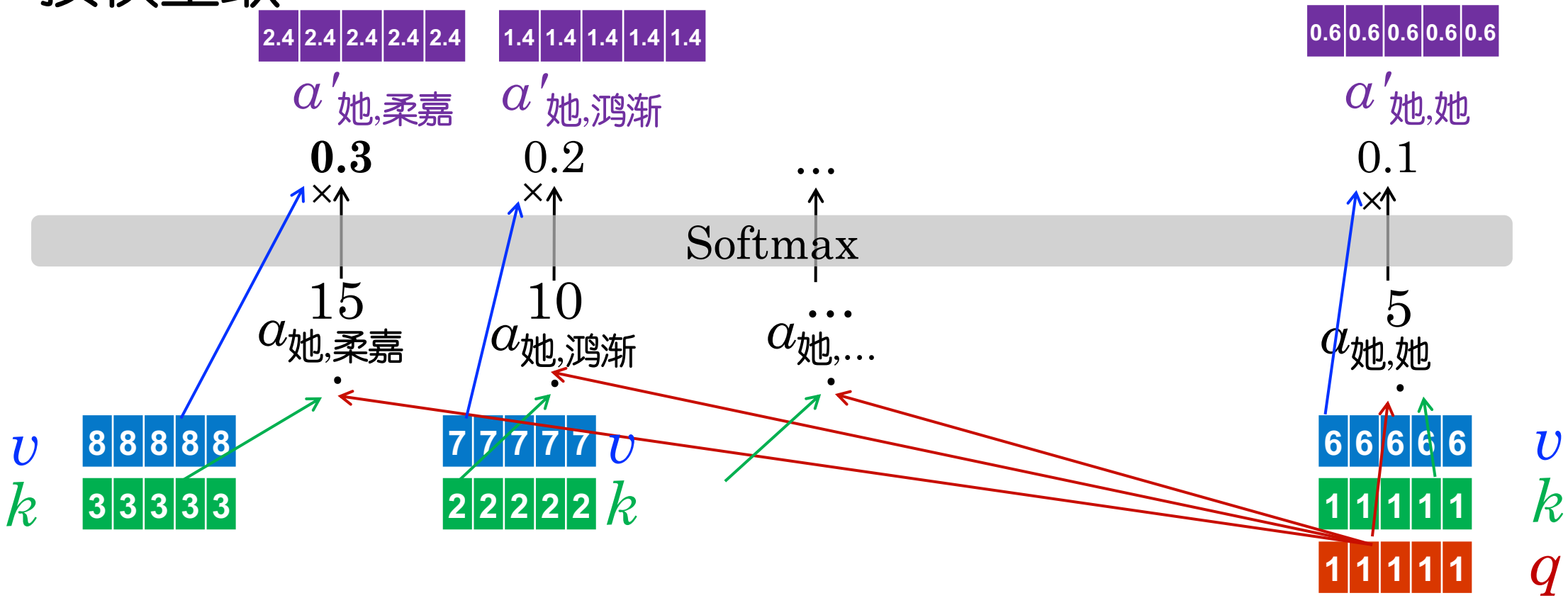


LSTM



如何快速读取所注意词的信息

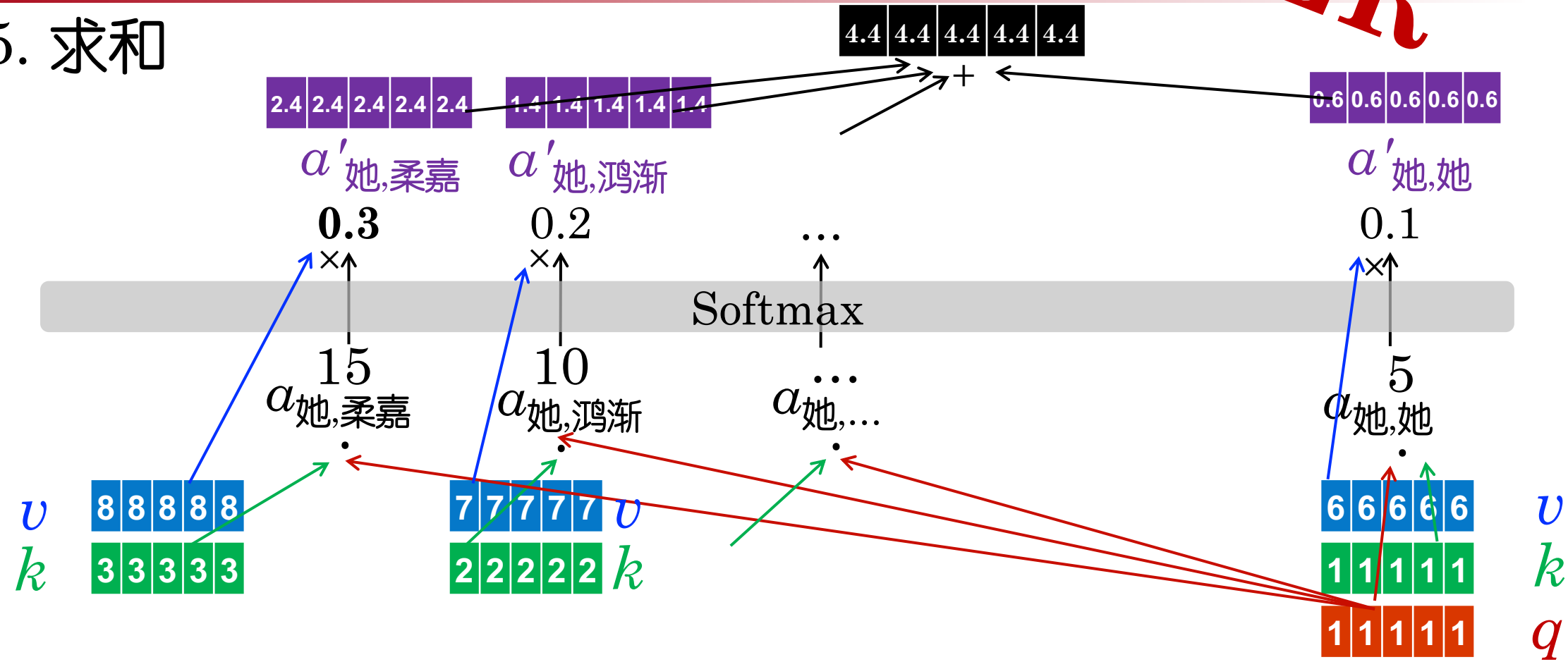
4. 按权重取*Value*



那时候， 柔嘉在家里等鸿渐回家来吃晚饭， 希望他会跟北母和好， 到她厂里做事

如何快速读取所注意词的信息 OVER

5. 求和



那时候， 柔嘉在家里等鸿渐回家来吃晚饭， 希望他会跟妆母和好， 到她厂里做事

如何使用所注意词的信息

无它

1. 拼接：

2. 相加：

那时候， 柔嘉在家里等鸿渐回家来吃晚饭， 希望他会跟妆母和好， 到她厂里做事

还有第三条路

我是效率控，多一次加法也不行！

4.4	4.4	4.4	4.4	4.4

演化
在寻找、读取过程中，
同步更新了“她”的原始编码！

5	5	5	5	5

那时候，柔嘉在家里等鸿渐回家来吃晚饭，希望他会跟北母和好，到她厂里做事

精巧的方法

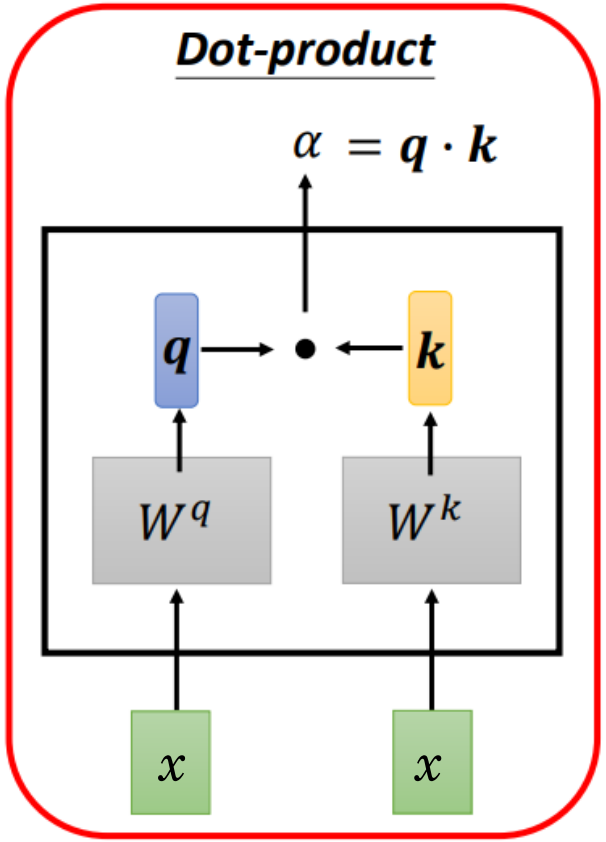
q, k, v从x孵化而来

$$q = x \cdot Wq$$

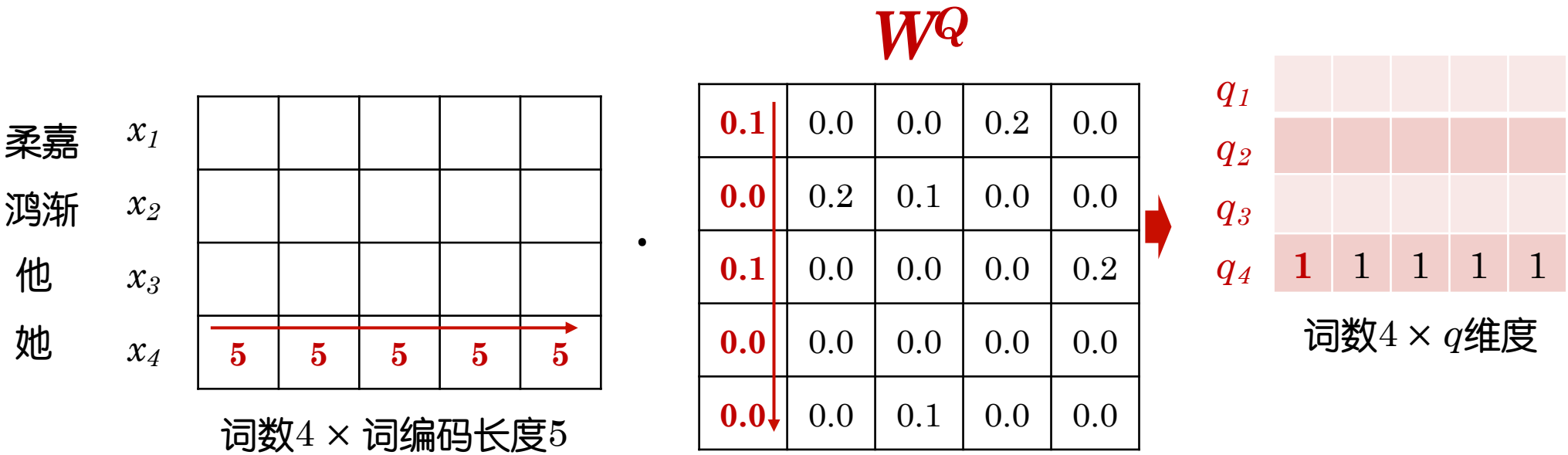
$$\mathrm{k} = x \cdot Wk$$

$$v = x \cdot Wv$$

模型参数



支持Q孵化有W^Q矩阵



词数4 × 词编码长度5

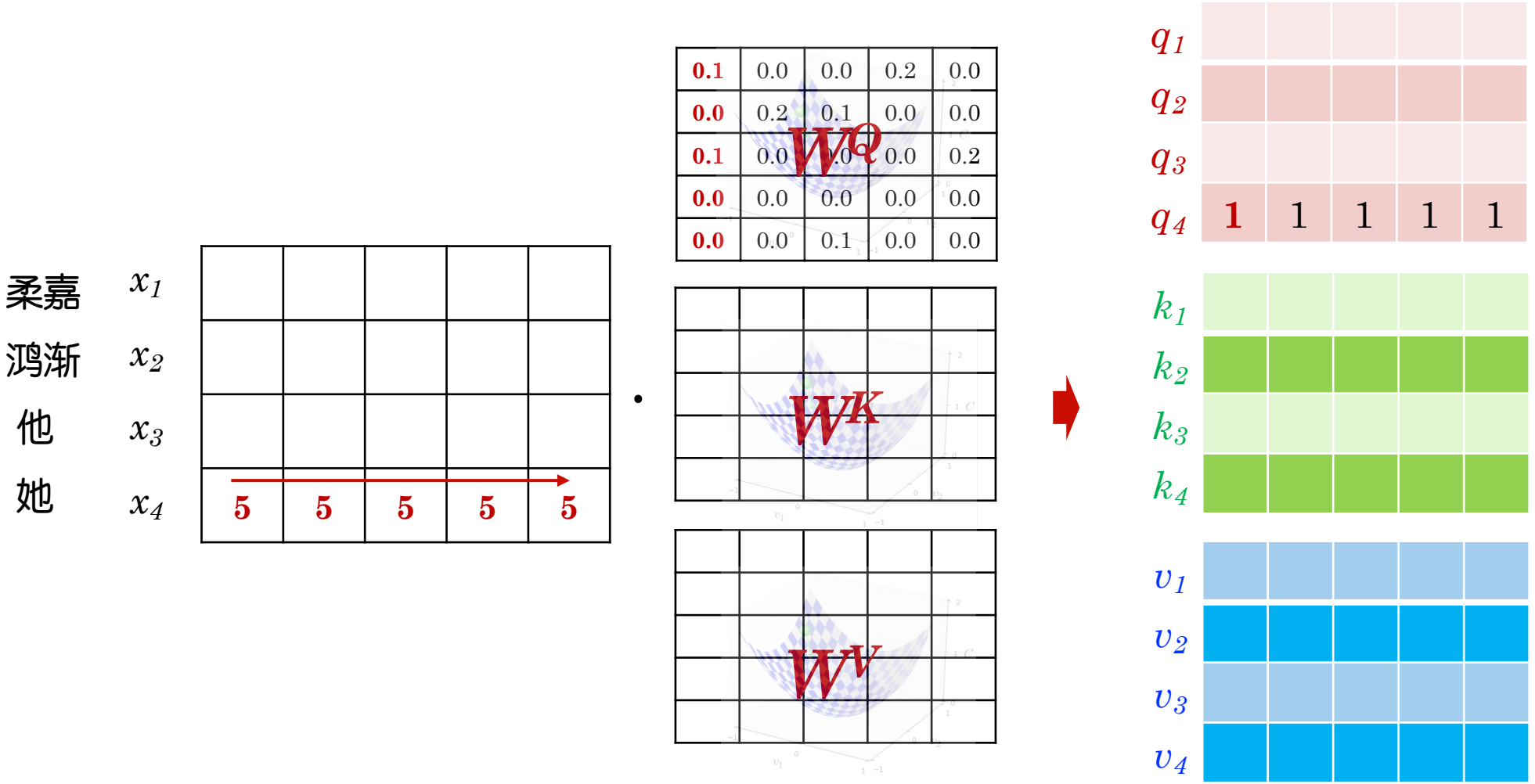
词编码长度5 ×q维度5

（q维度此处等于词编码长度，

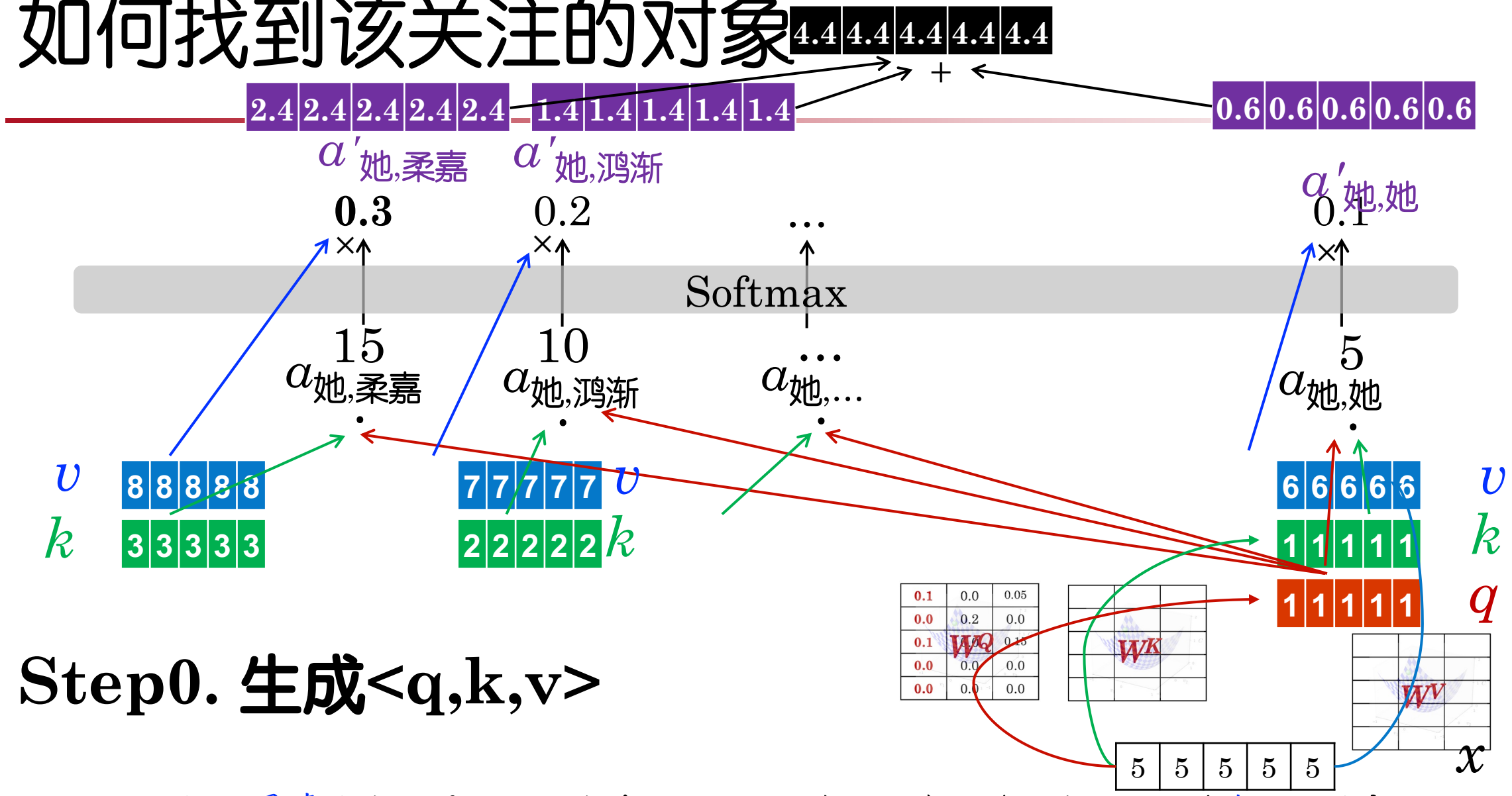
但也可以不相等）

词数4 × q维度

还有W^K, W^V“孵化”矩阵，都是模型参数



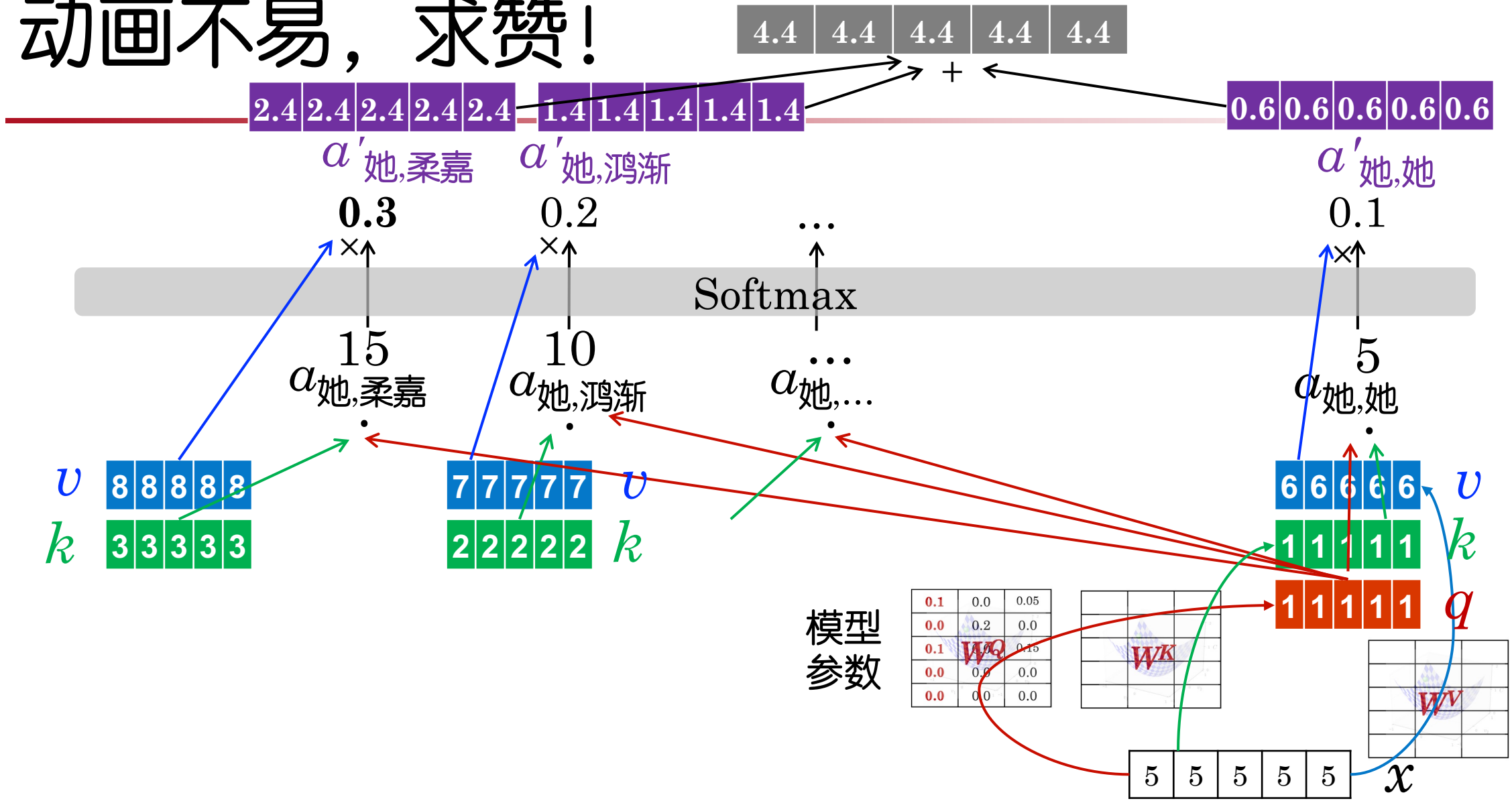
如何找到该关注的对象



Step0. 生成<q,k,v>

那时候， 柔嘉在家里等鸿渐回家来吃晚饭， 希望他会跟妯娌和好， 到她厂里做事

动画不易，求赞！



那时候， 柔嘉在家里等鸿渐回家来吃晚饭， 希望他会跟妳母和好， 到她厂里做事

演化

在寻找、读取过程中，
“她”同步更新了自己的原始编码，
将自己关心的人融入自己的编码！

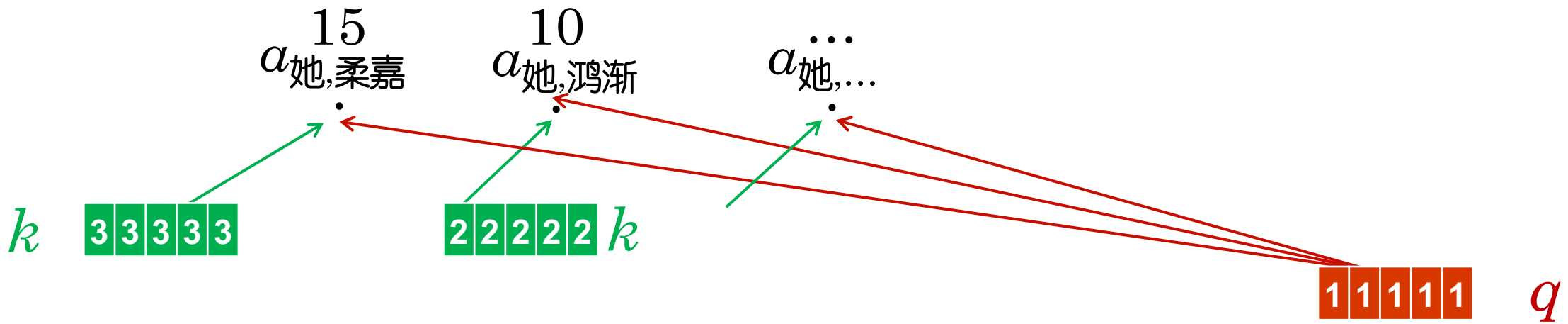
她不再是一个人在战斗！

那时候， 柔嘉在家里等鸿渐回家来吃晚饭， 希望他会跟妯娌和好， 到她厂里做事

Trick：缩放 – 消除<q,k,v>向量长度影响

1. 计算w_i对所有w_j的**注意力分数**： $\alpha_{i,j} = q^i \cdot k^j$

q,k内积的方差与维度线形正比，太大时Softmax分布极其“尖锐”

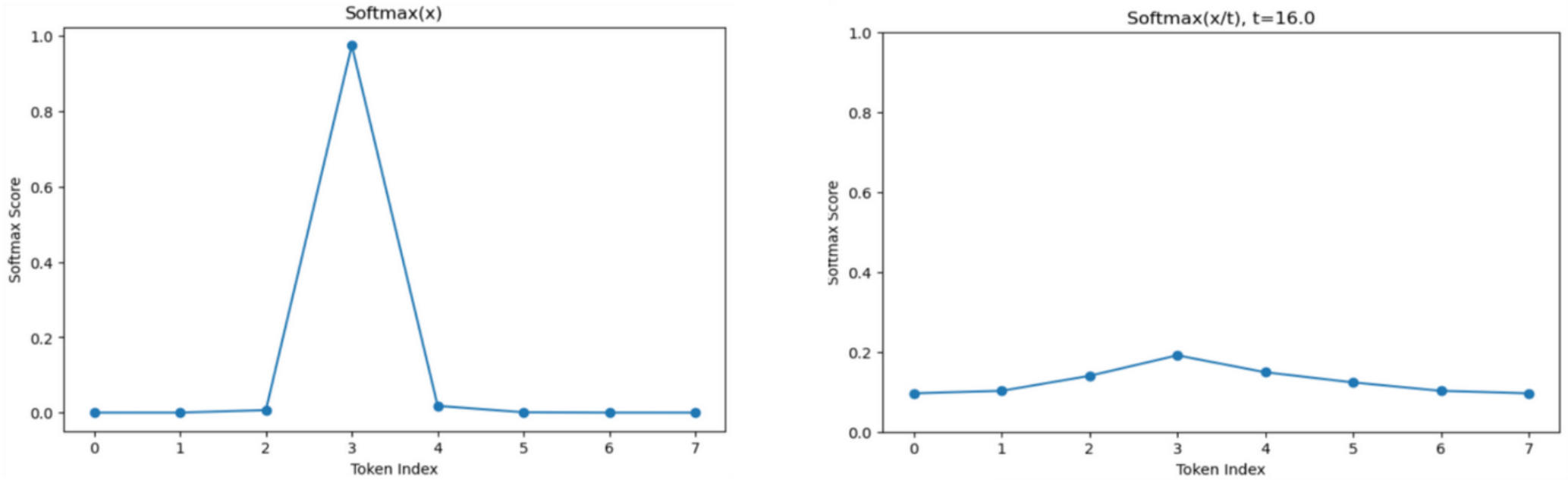


那时候， 柔嘉在家里等鸿渐回家来吃晚饭， 希望他会跟北母和好， 到她厂里做事

Trick：缩放 – 消除<q,k,v>向量长度影响

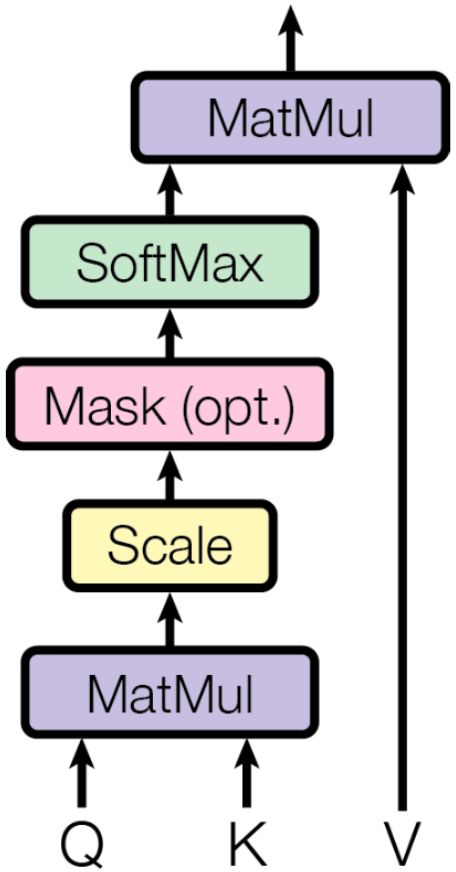
1. 计算w_i对所有w_j的**注意力分数**： $\alpha_{i,j} = q^i \cdot k^j$

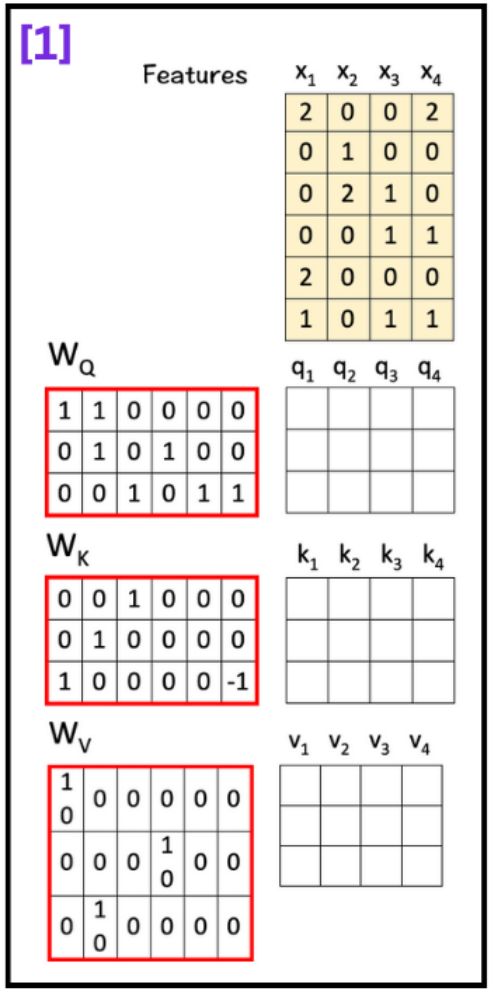
q,k内积的方差与维度线形正比，太大时Softmax分布极其“尖锐”

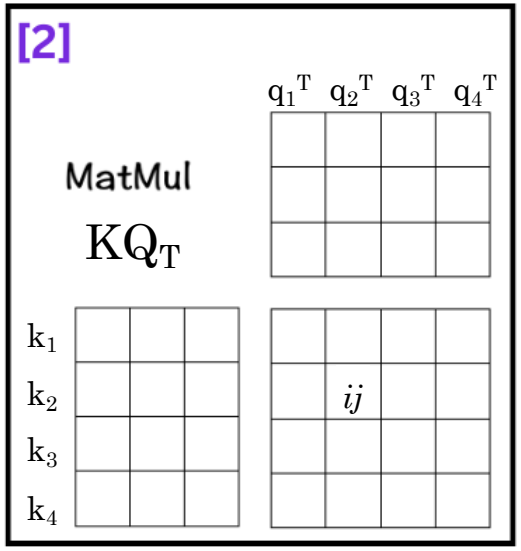


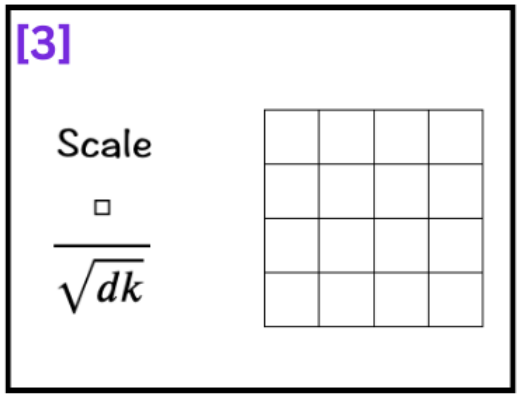
[1, 2, 7, 12, 8, 5, 2, 1]

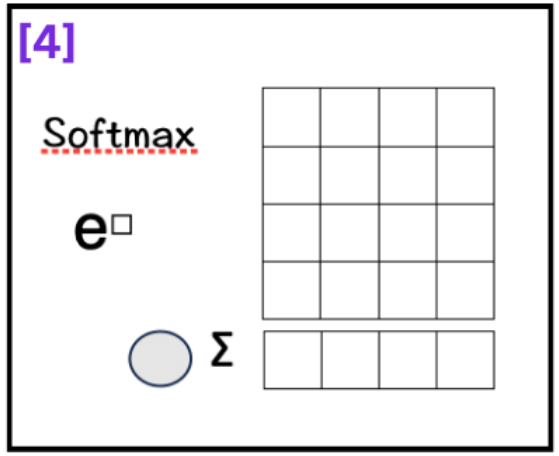
Self-Attention过程一览

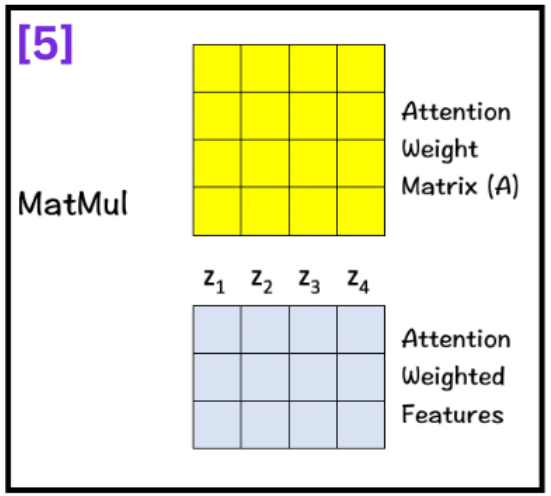










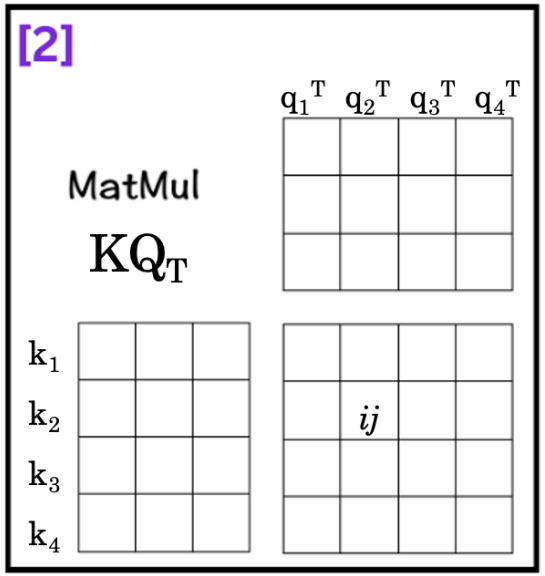


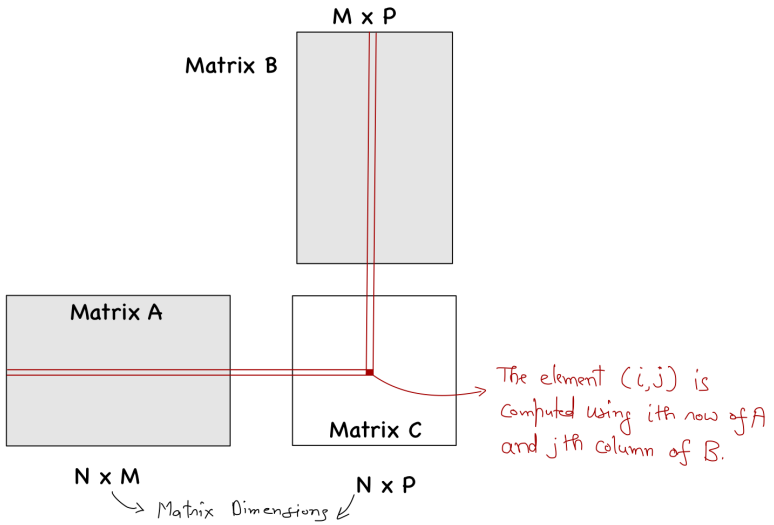
Self-Attention的数学表示

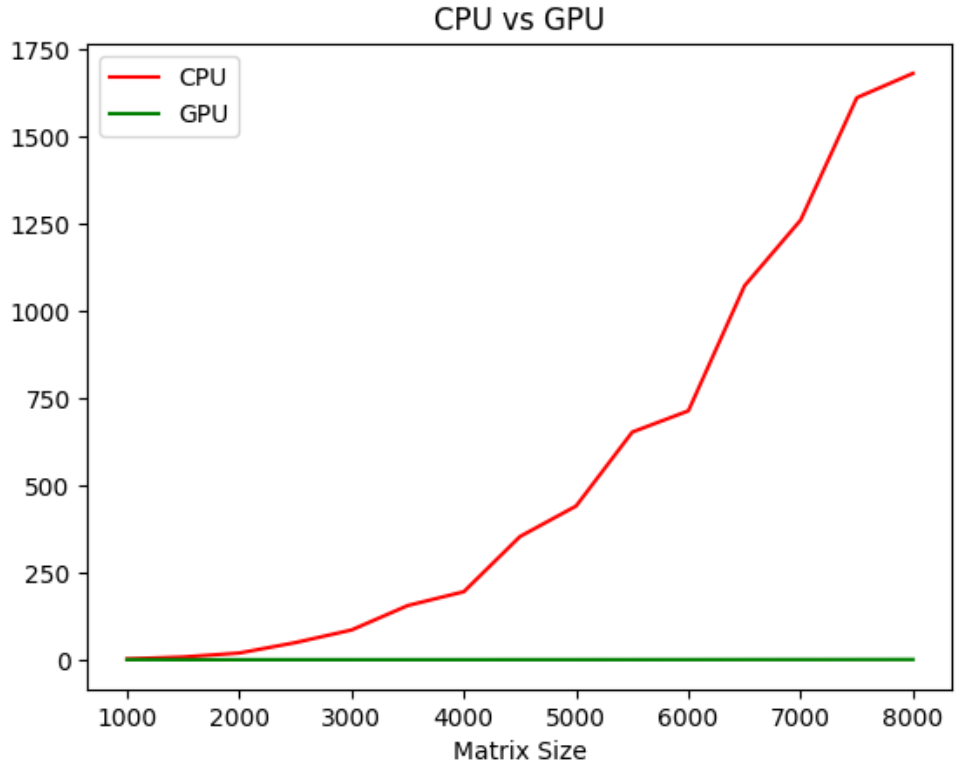
$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

Vaswani, Ashish, et al. "Attention is all you need." *Advances in neural information processing systems* 30 (2017).

并发能力：GPU善于处理矩阵运算



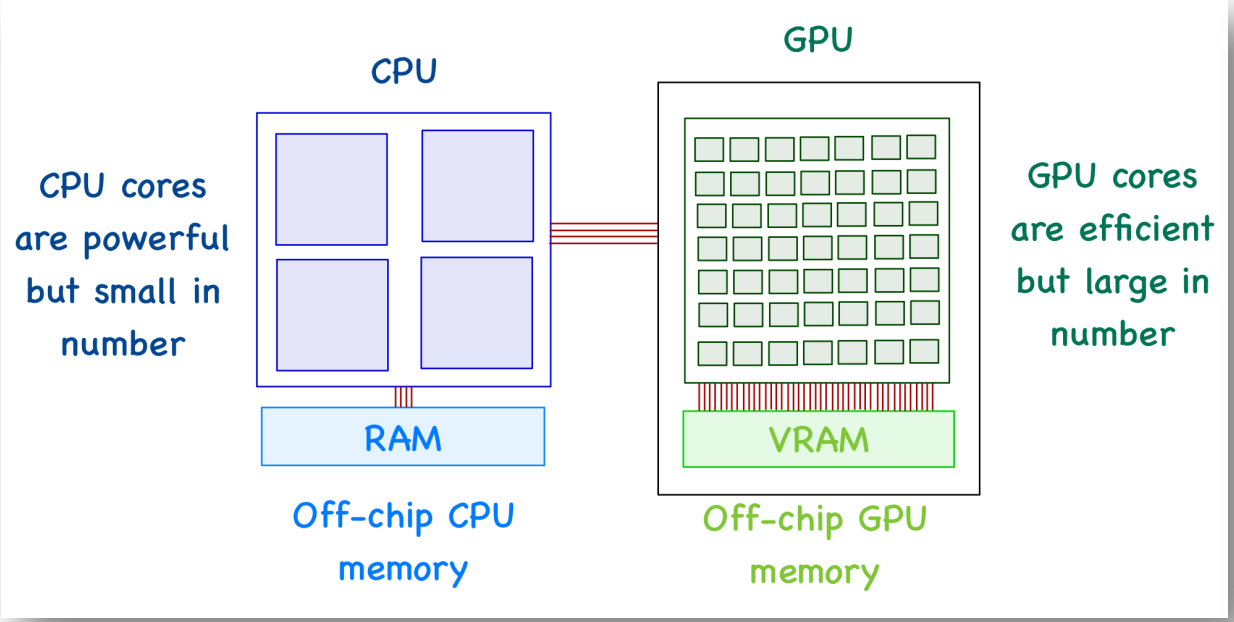


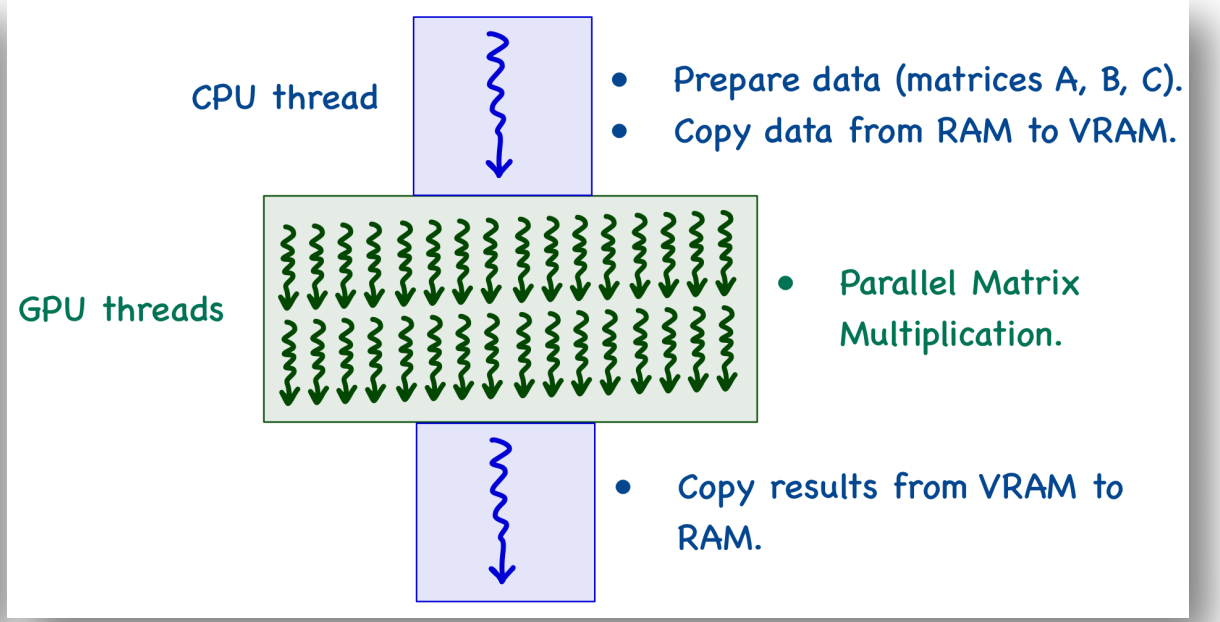


一次矩阵乘法，算出所有词之间的两两注意力

而GPU非常善于矩阵运算

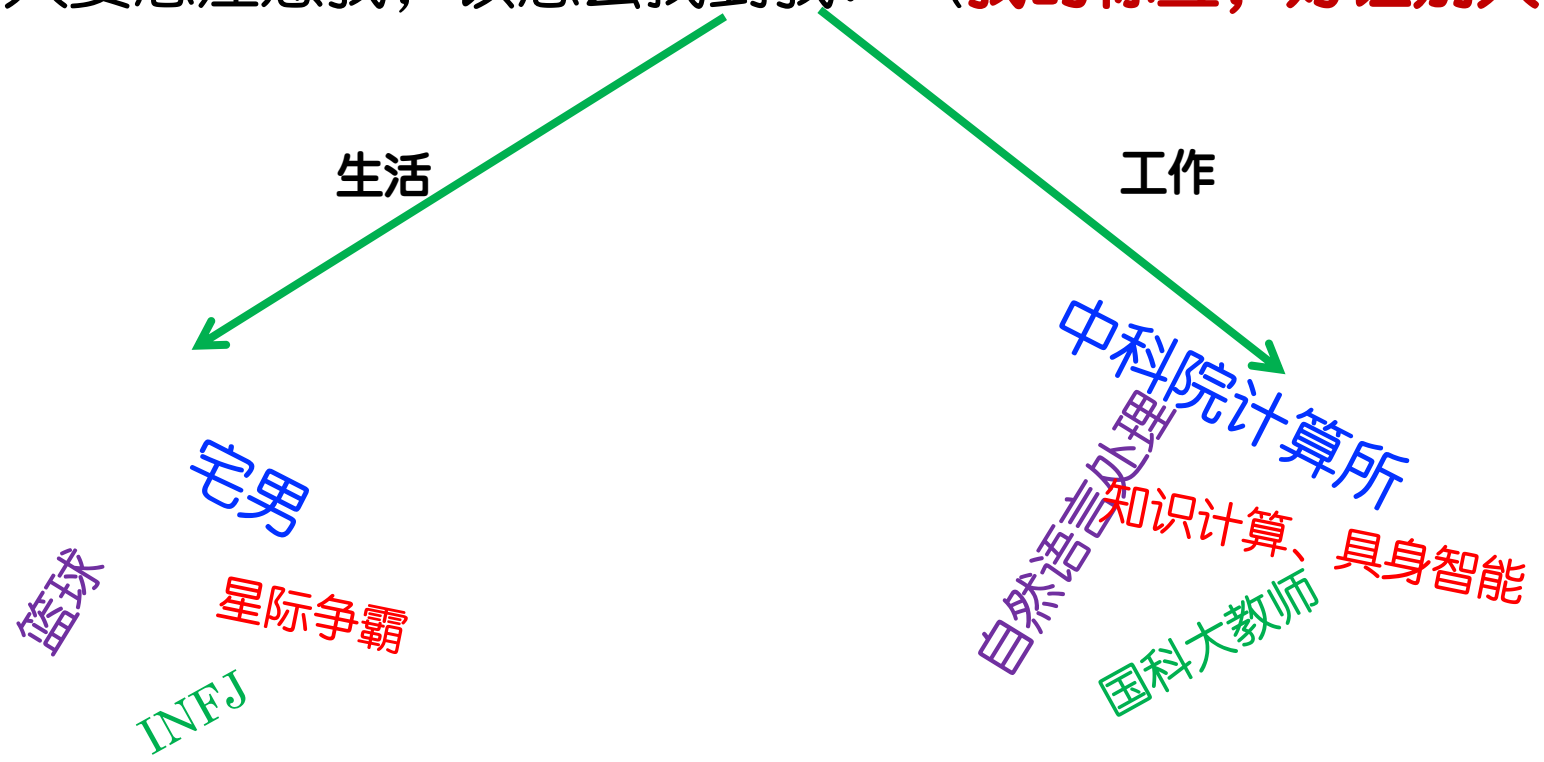
并发能力：GPU善于处理矩阵运算





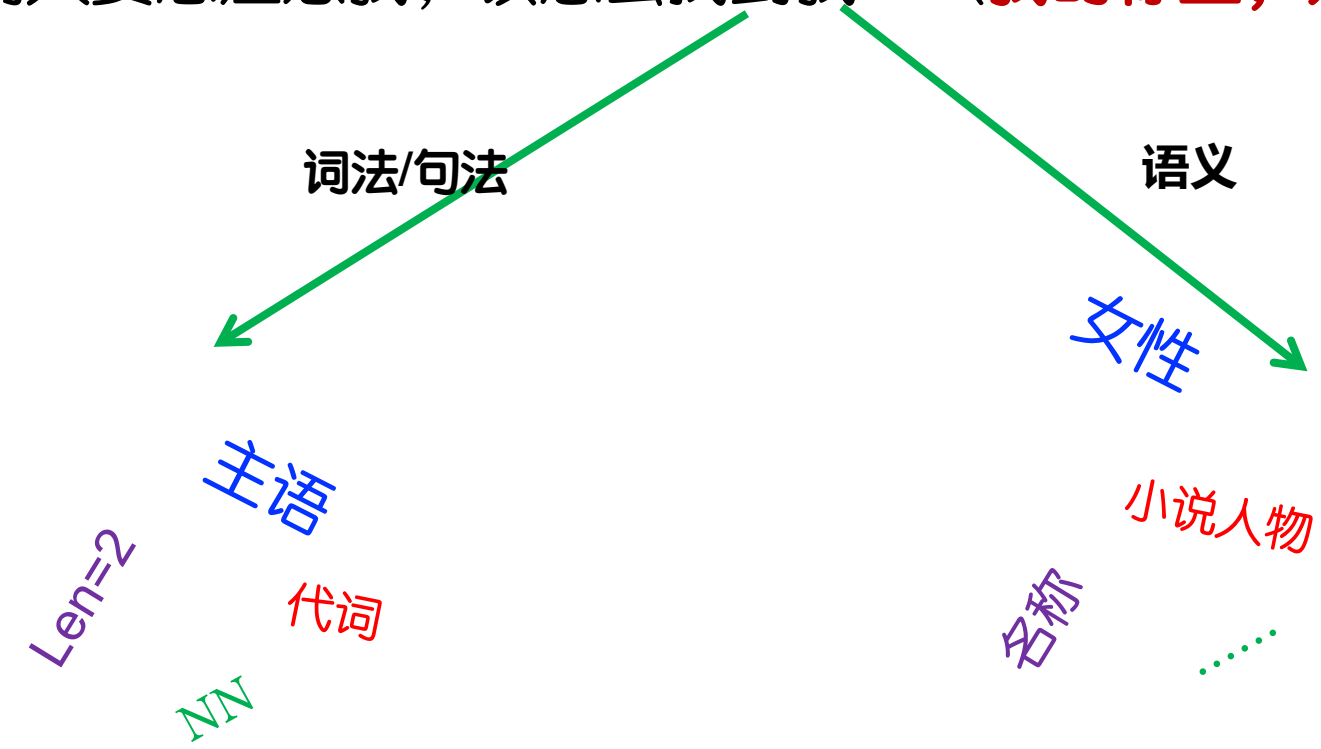
问题1：当我有两套标签，别人怎么找我?

- 别人要想注意我，该怎么找到我？ （**我的标签，好让别人也能要回答**）

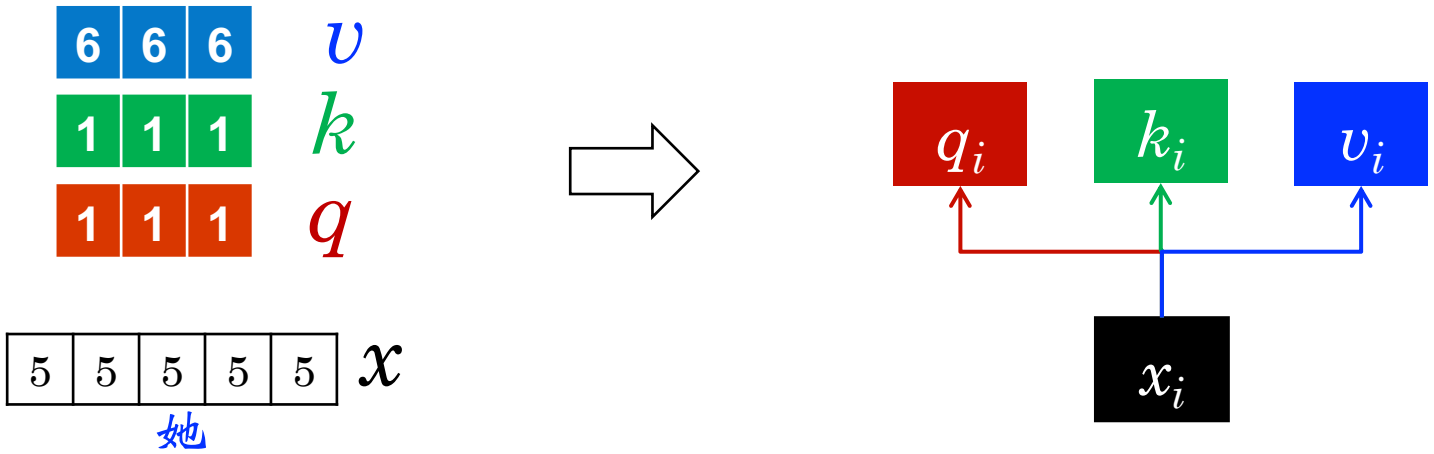


问题1：当我有两套标签，别人怎么找我?

- 别人要想注意我，该怎么找到我？ （**我的标签，好让别人也能要回答**）

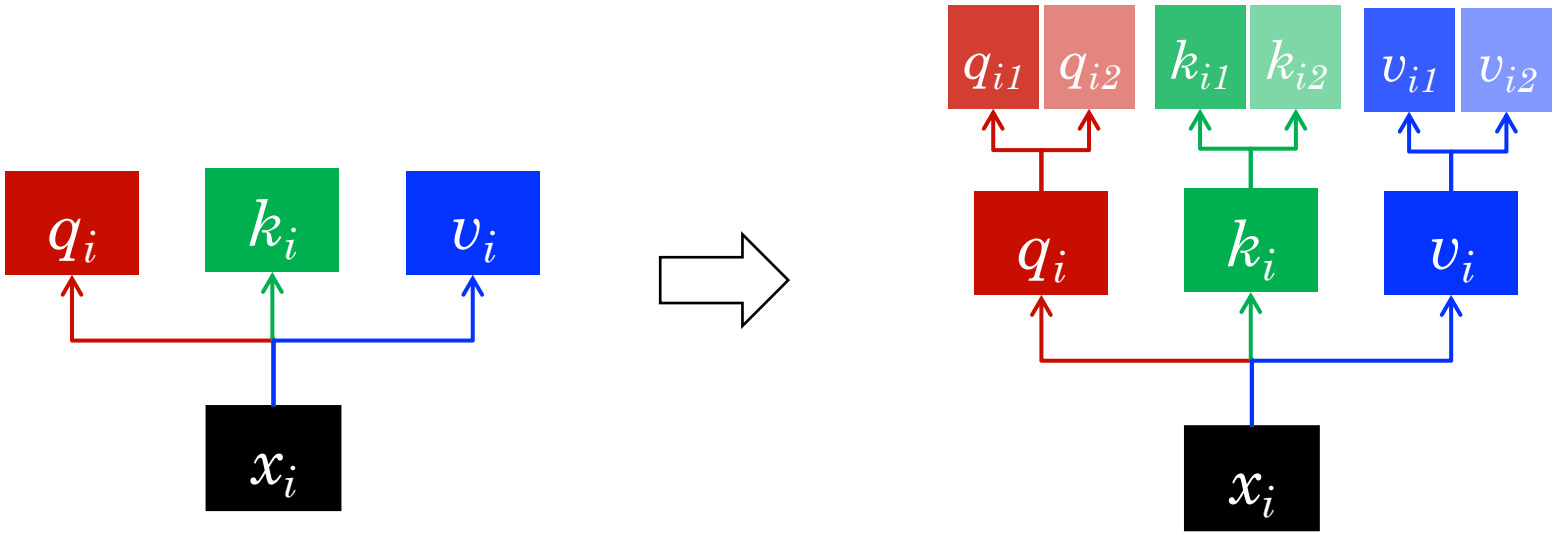


Self-attention简化表示



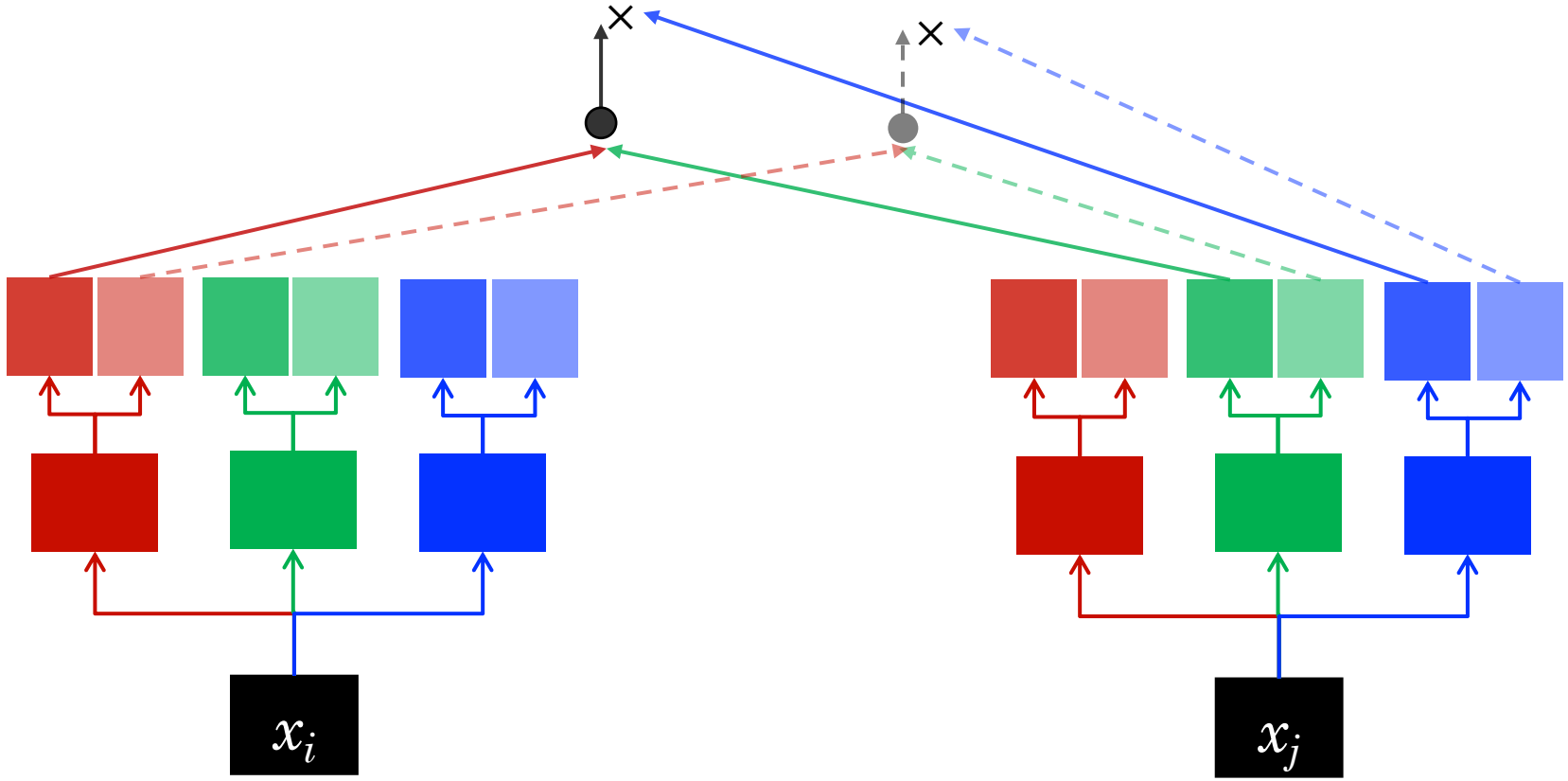
Multi-head Self-attention

一个注意力的维度不够，那就多个维度，各自单独使用



Multi-head Self-attention

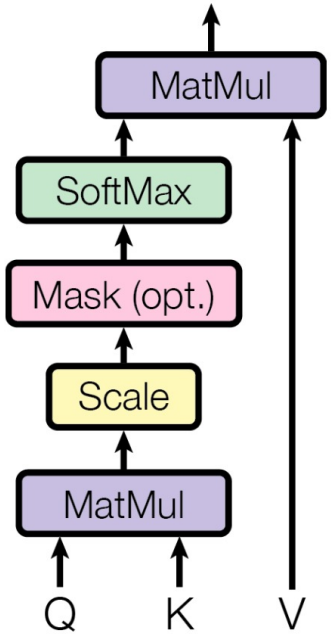
一个注意力的维度不够，那就多个维度，**各自单独使用**



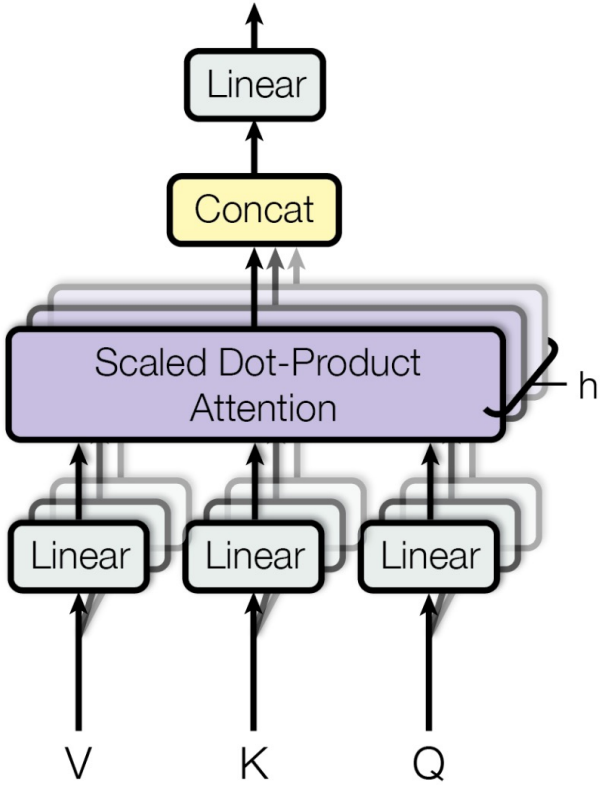
Multi-head Self-attention

一个注意力的维度不够，那就多个维度，**各自单独使用**

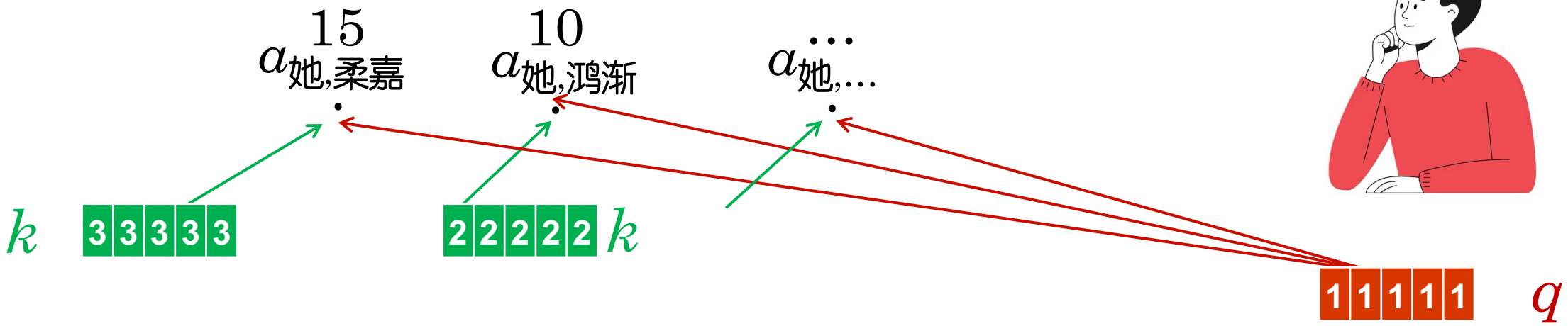
Scaled Dot-Product Attention



Multi-Head Attention



自注意力有什么缺点?



那时候， 柔嘉在家里等鸿渐回家来吃晚饭， 希望他会跟妆母和好， 到她厂里做事

那时候， 柔嘉在家里等鸿渐回家来吃晚饭， 希望他到她厂里做事

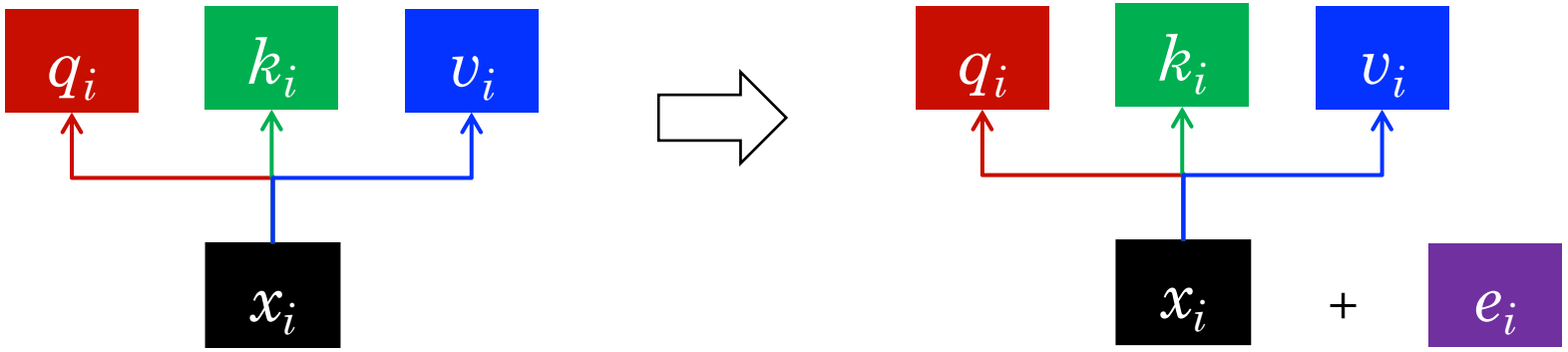
注意力权重跟词之间的距离无关?

中国科学院大学
University of Chinese Academy of Sciences

目 录

方法1：可训练的绝对位置编码

- 自注意力对每个词增加了一个它独特的“位置编码”
- 典型模型：BERT



$$\text{input}_i = \text{token\_embed}_i + \text{pos\_embed}_i$$

方法1：可训练的绝对位置编码

- 缺点：无“外推”能力
  - 训练时句子最长5个字，来了7个字的不会了？
  - 只寻到了距离<5的字对注意力权重的影响

风劲角弓鸣，
将军猎渭城。

?

风急天高猿啸哀，
渚清沙白鸟飞回。

方法2：Sinusoidal（三角函数式）位置编码

- 将位置编码为正弦余弦函数
- 原始Transformer使用

Position Embedding 是一个向量

Position 词的位置

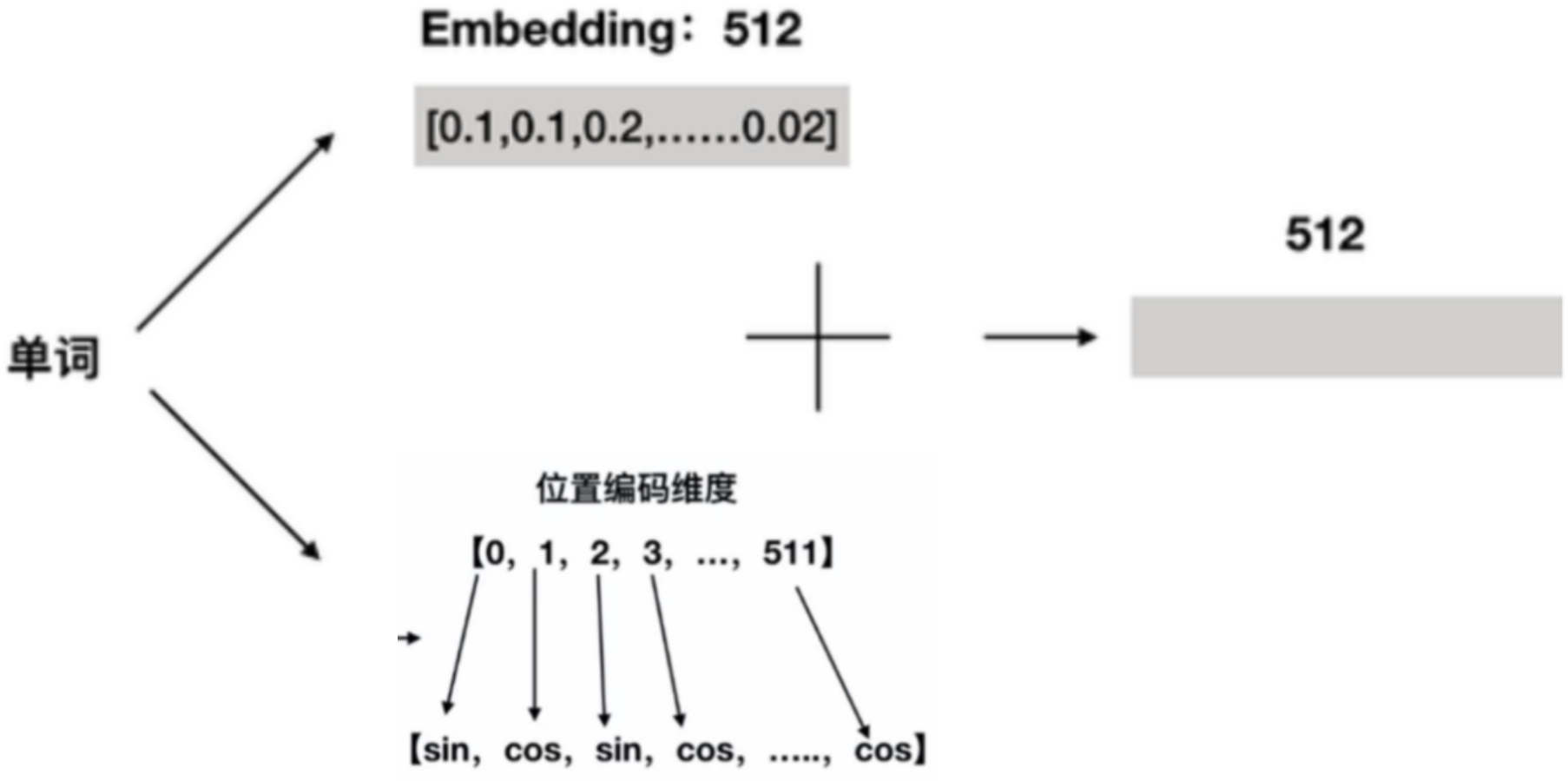
向量的元素下标

token编码长度

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

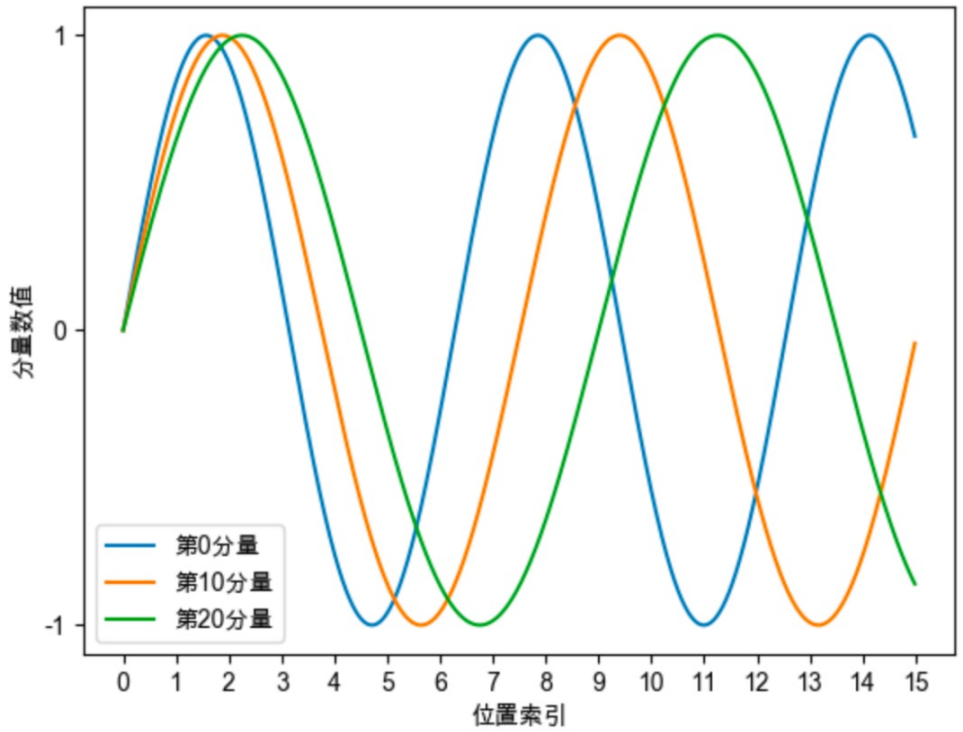
$$PE_{(pos,2i+1)} = cos(pos/10000^{2i/d_{\text{model}}})$$

方法2：Sinusoidal（三角函数式）位置编码

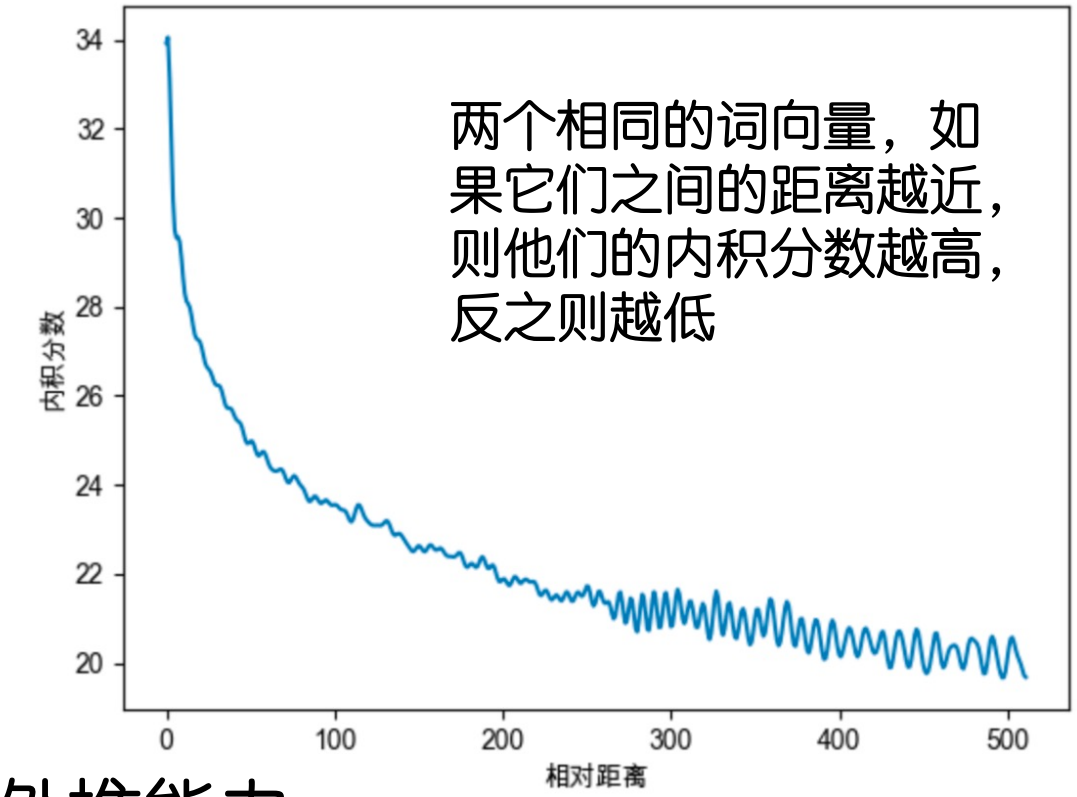


方法2：Sinusoidal（三角函数式）位置编码

❒ 性质1：周期性



❒ 性质2：衰减性

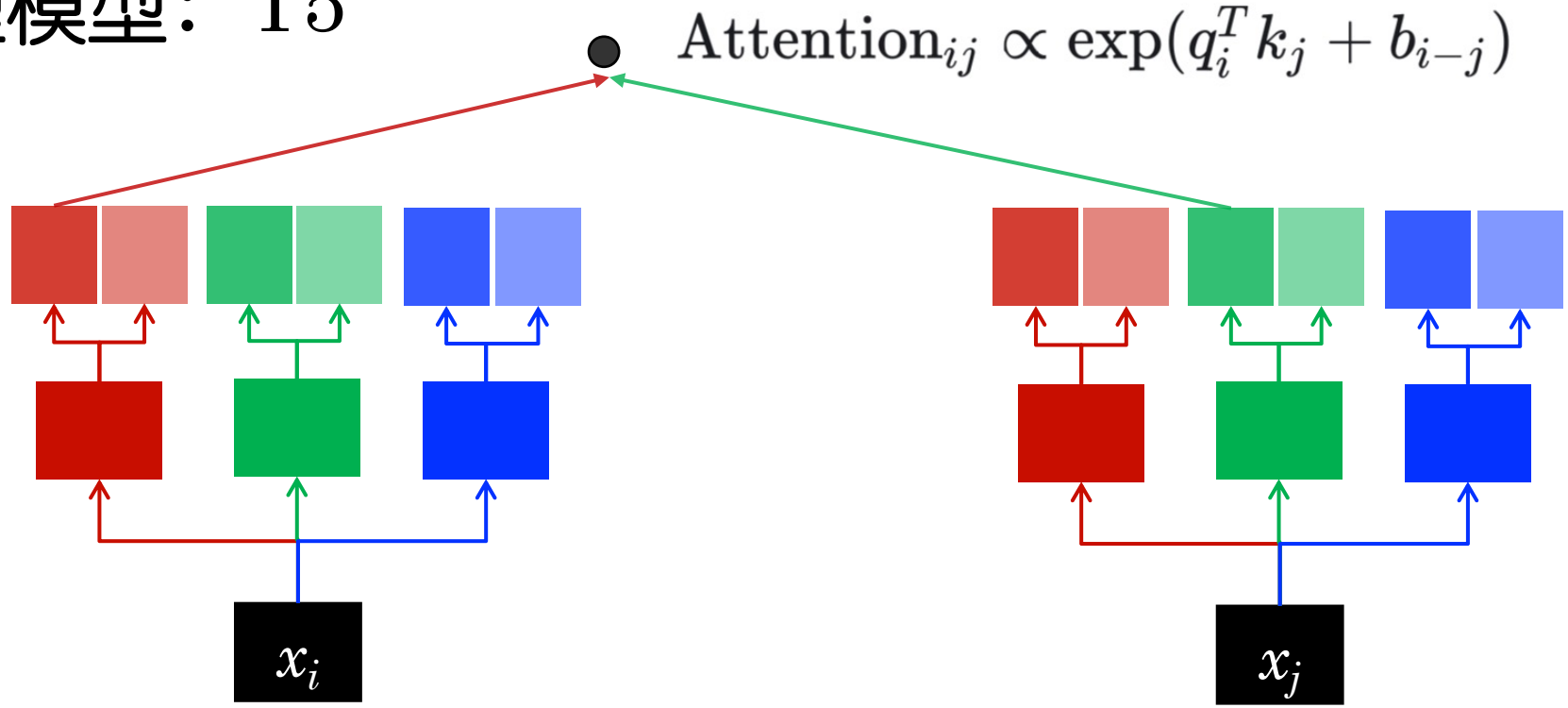


两个相同的词向量，如果它们之间的距离越近，则他们的内积分数越高，反之则越低

产生一定的外推能力

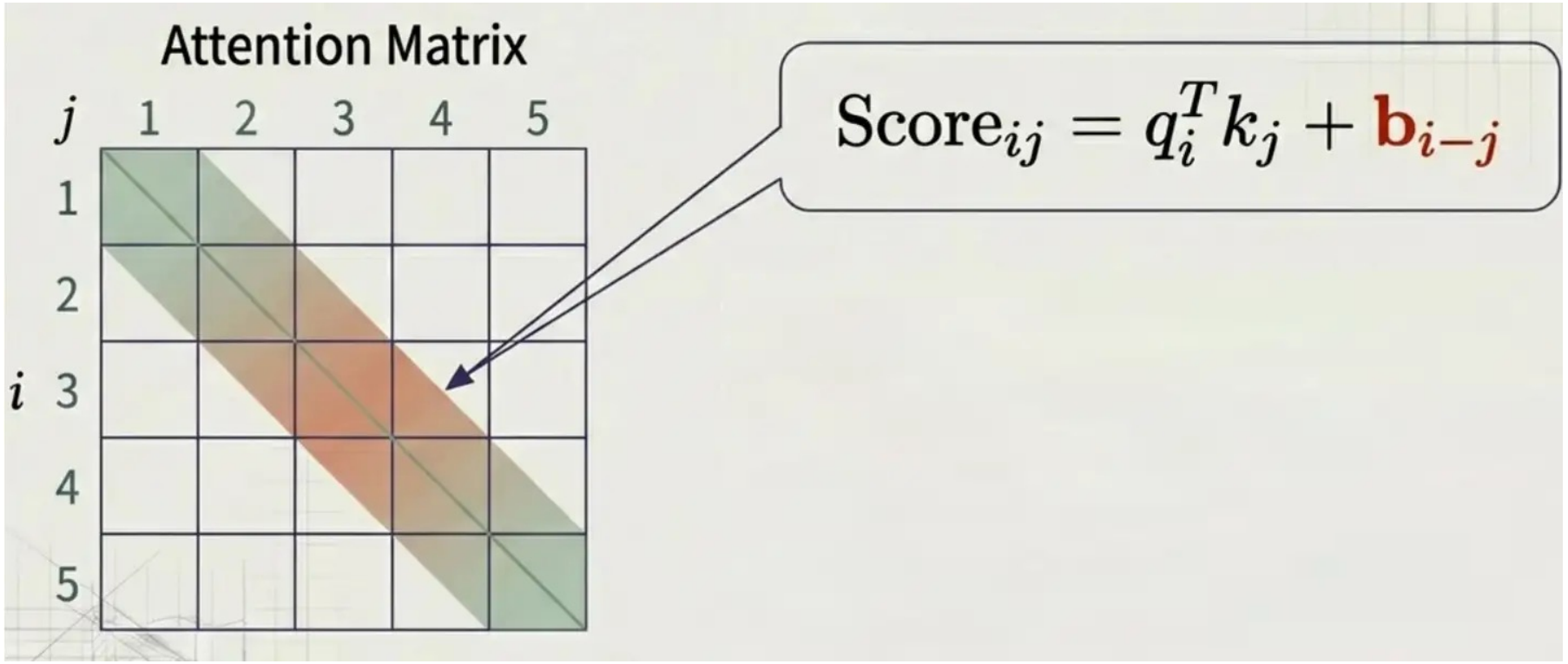
方法3：相对位置编码

- 在计算attention时，加入一个只依赖于相对位置的偏置
- 典型模型：T5



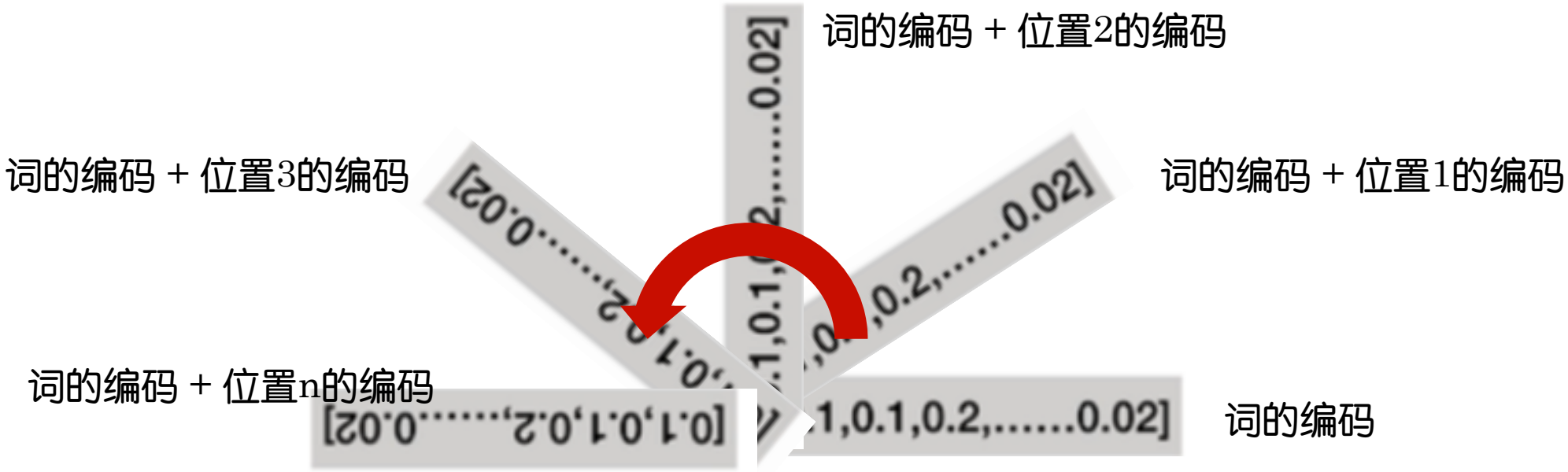
方法3：相对位置编码

- 在计算attention时，加入一个只依赖于相对位置的偏置
- 典型模型：T5



方法4：RoPE（Rotary Position Embedding旋转位置编码）

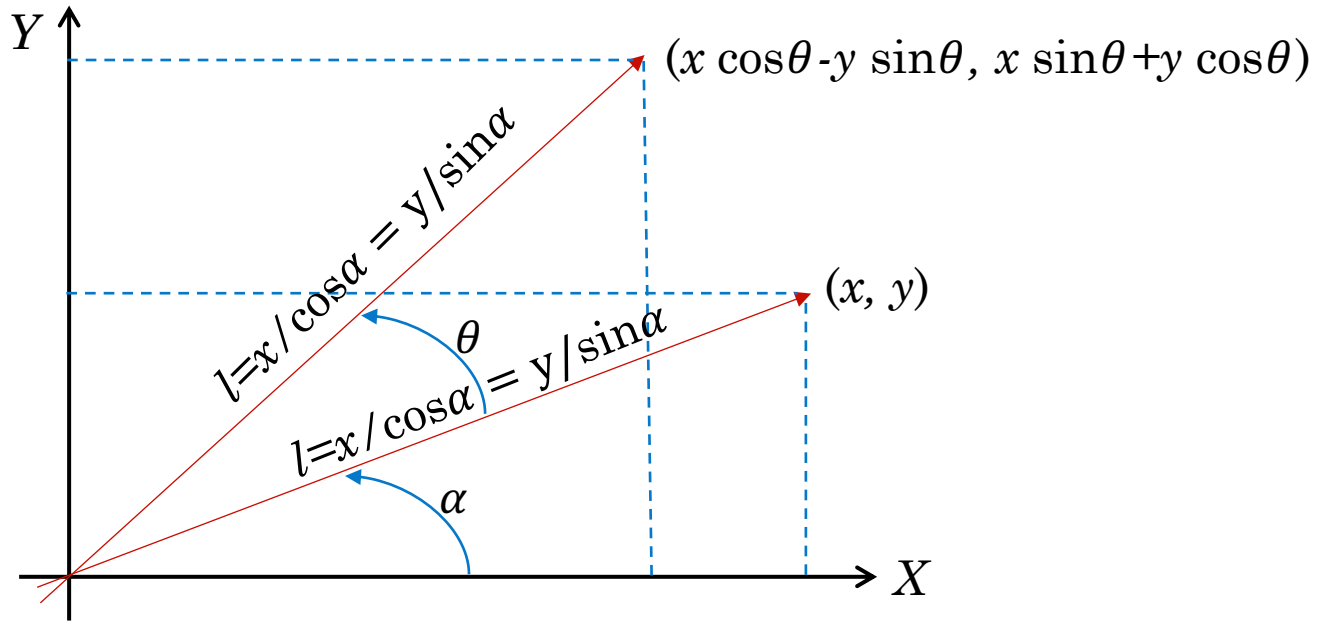
- 思想：通过绝对位置编码的方式实现相对位置编码
- 方法：将一个向量旋转某个角度代表位置信息
- 目前LLM的主流选择：LLaMA、GPT、ChatGLM



方法4：RoPE（Rotary Position Embedding旋转位置编码）

❒ 将一个向量旋转某个角度代表位置信息

1. 词编码为(x, y)，在笛卡尔空间表示为向量（一个带有方向和长度的量）
2. (x, y)逆时针旋转θ度后坐标如图



- 向量长度$l = x/\cos\alpha = y/\sin\alpha$
- $x' = l\cos(\alpha+\theta)$

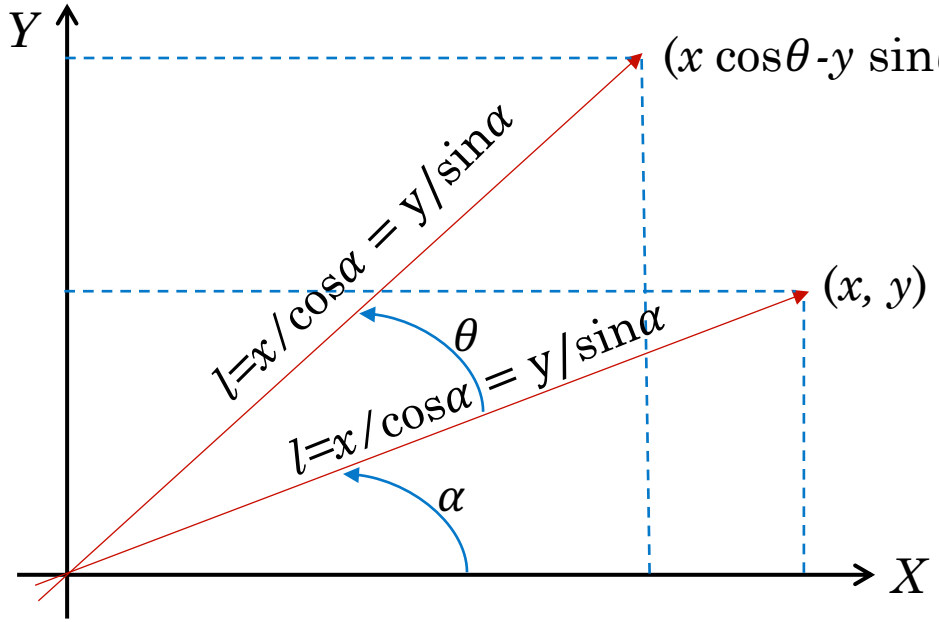
  $= l(\cos\alpha\cdot\cos\theta - \sin\alpha\cdot\sin\theta)$

  $= x\cos\theta - y\sin\theta$
- $y' = x\sin\theta + y\cos\theta$

方法4：RoPE（Rotary Position Embedding旋转位置编码）

❒ 将一个向量旋转某个角度代表位置信息

1. 词编码为(x, y)，在笛卡尔空间表示为向量（一个带有方向和长度的量）
2. (x, y)逆时针旋转θ度后坐标如图



$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

旋转矩阵

方法4：RoPE（Rotary Position Embedding旋转位置编码）

❒ 将一个向量旋转某个角度代表位置信息

Tips：
$a \cdot b = a^T * b$

旋转$m\theta$和$n\theta$后两个向量的点积（**相似度**），等于旋转了$(n\text{-}m)\theta$的角度（**相对位置**）

$$\left(\begin{bmatrix}\cos m\theta & -\sin m\theta \\ \sin m\theta & \cos m\theta\end{bmatrix}\right)\cdot\left(\begin{bmatrix}\cos n\theta & -\sin n\theta \\ \sin n\theta & \cos n\theta\end{bmatrix}\right)$$

$$=\begin{bmatrix}\cos m\theta & \sin m\theta \\ -\sin m\theta & \cos m\theta\end{bmatrix}\times\begin{bmatrix}\cos n\theta & -\sin n\theta \\ \sin n\theta & \cos n\theta\end{bmatrix}$$

$$=\begin{bmatrix}\cos m\theta\cos n\theta+\sin m\theta\sin n\theta & \cos m\theta\cos n\theta-\cos m\theta\sin n\theta \\ \cos m\theta\cos n\theta-\sin m\theta\cos n\theta & \cos m\theta\cos n\theta+\sin m\theta\sin n\theta\end{bmatrix}$$

$$=\begin{bmatrix}\cos(n-m)\theta & -\sin(n-m)\theta \\ \sin(n-m)\theta & \cos(n-m)\theta\end{bmatrix}$$

两个词离得越近

= 相似度越高

= 相对旋转角度越小

方法4：RoPE（Rotary Position Embedding旋转位置编码）

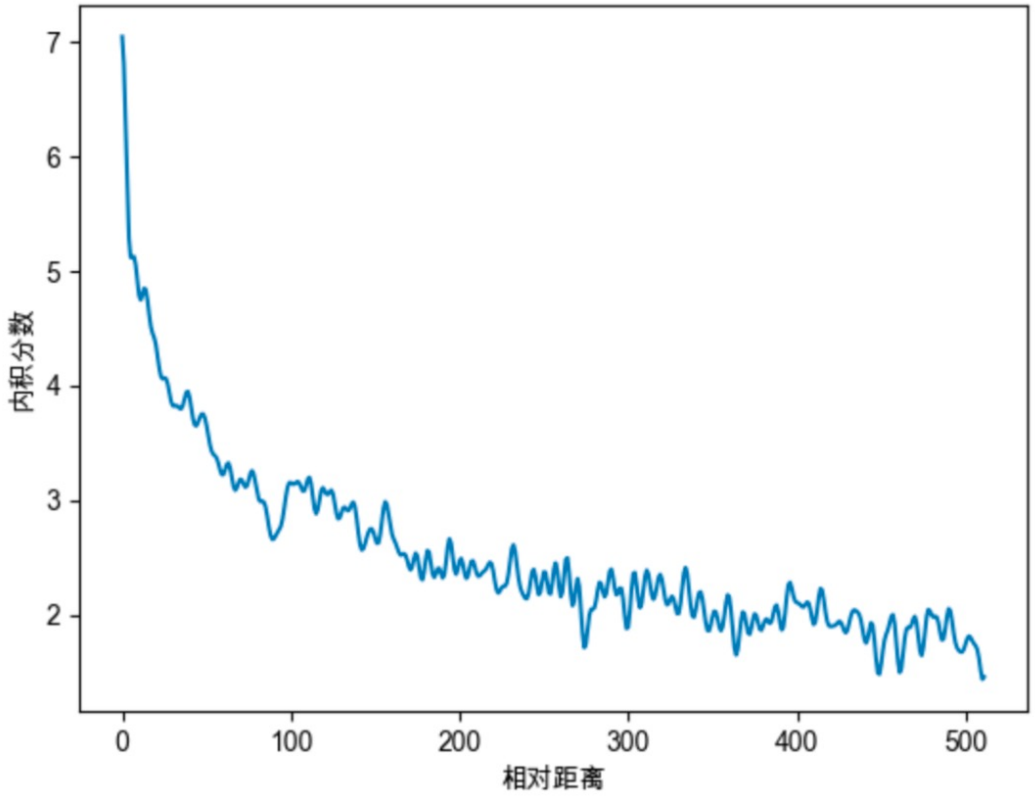
❒ 将一个向量旋转某个角度代表位置信息

词编码是多维时，分解为两两一组旋转即可

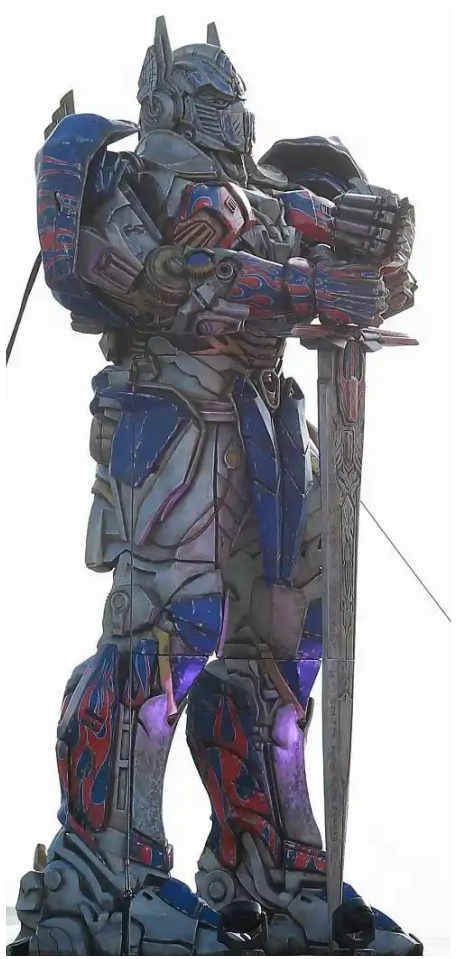
$$\begin{pmatrix} \cos m\theta & -\sin m\theta & 0 & 0 & \cdots & 0 & 0 \\ \sin m\theta & \cos m\theta & 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & \cos m\theta & -\sin m\theta & \cdots & 0 & 0 \\ 0 & 0 & \sin m\theta & \cos m\theta & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & \cos m\theta & -\sin m\theta \\ 0 & 0 & 0 & 0 & \cdots & \sin m\theta & \cos m\theta \end{pmatrix} \begin{pmatrix} q_0 \\ q_1 \\ q_2 \\ q_3 \\ \vdots \\ q_{d-2} \\ q_{d-1} \end{pmatrix}$$

方法4：RoPE（Rotary Position Embedding旋转位置编码）

❒ 衰减性



随机初始化两个向量q和k，将q固定在位置0上，k的位置从0开始逐步变大，依次计算q和k之间的内积。我们发现随着q和k的相对距离的增加，它们之间的内积分数呈现出远程衰减的性质



1. 带注意力的Encoder-Decoder
2. 自注意力
3. 位置编码
4. Transformers

Attention Is All You Need

Attention is all you need

A Vaswani, N Shazeer, N Parmar… - Advances in neural …, 2017 - proceedings.neurips.cc

… to attend to all positions in the decoder up to and including that position. We need to prevent … We implement this inside of scaled dot-product attention by masking out (setting to −∞) …

☆ 保存 99 引用 被引用次数: 236405 相关文章 所有 71 个版本 »

Ashish Vaswani* Google Brain avaswani@google.com

Noam Shazeer* Google Brain noam@google.com

Niki Parmar* Google Research nikip@google.com

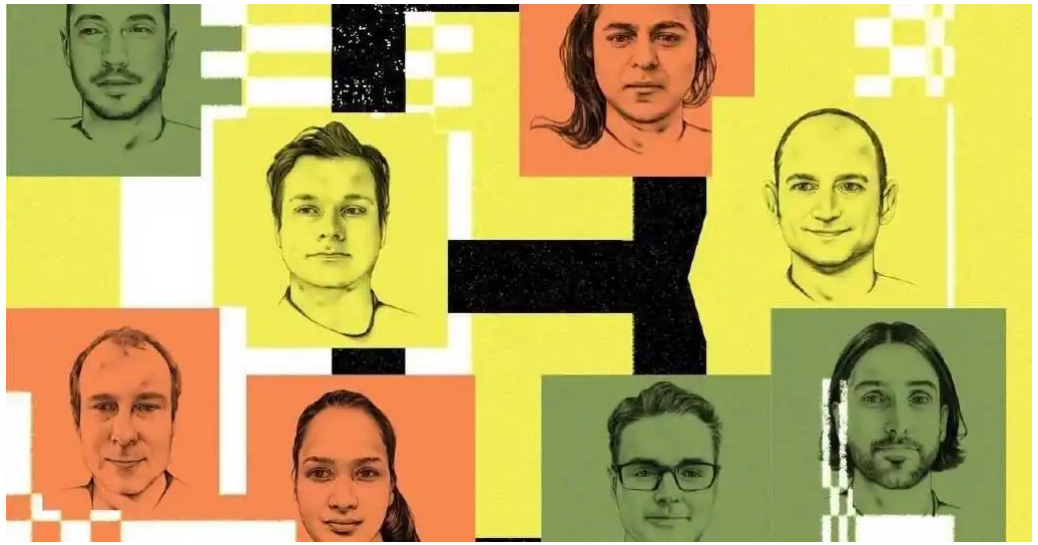
Jakob Uszkoreit* Google Research usz@google.com

Llion Jones* Google Research llion@google.com

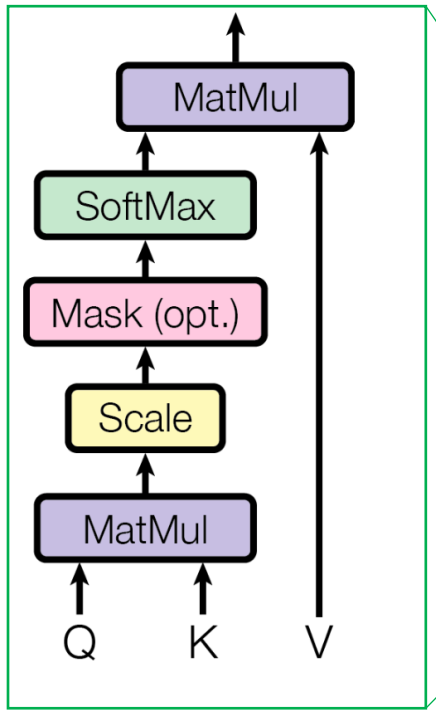
Aidan N. Gomez* † University of Toronto aidan@cs.toronto.edu

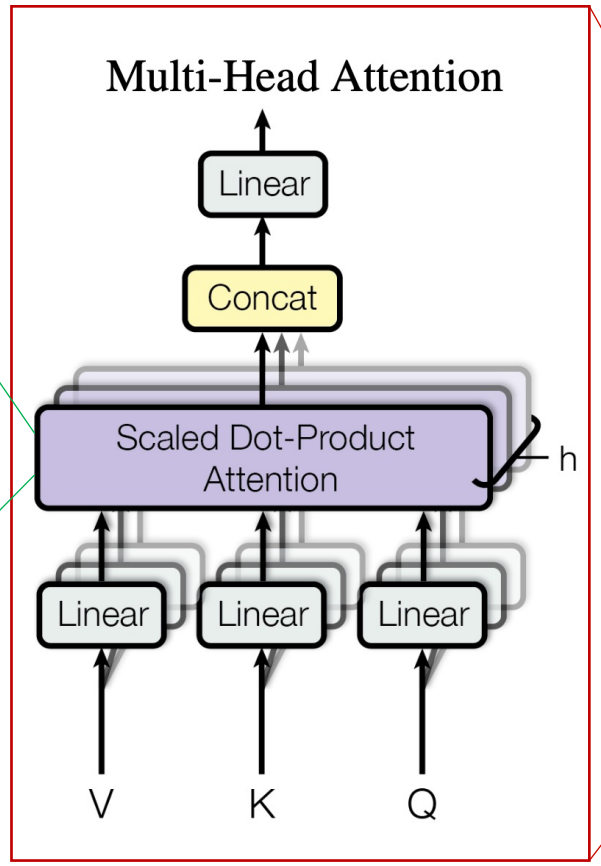
Łukasz Kaiser* Google Brain lukaszkaiser@google.com

Illia Polosukhin* ‡ illia.polosukhin@gmail.com

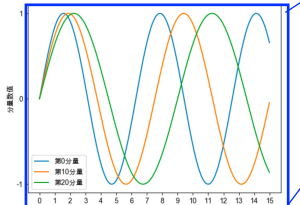


标准模型架构





Sinusoidal
位置编码



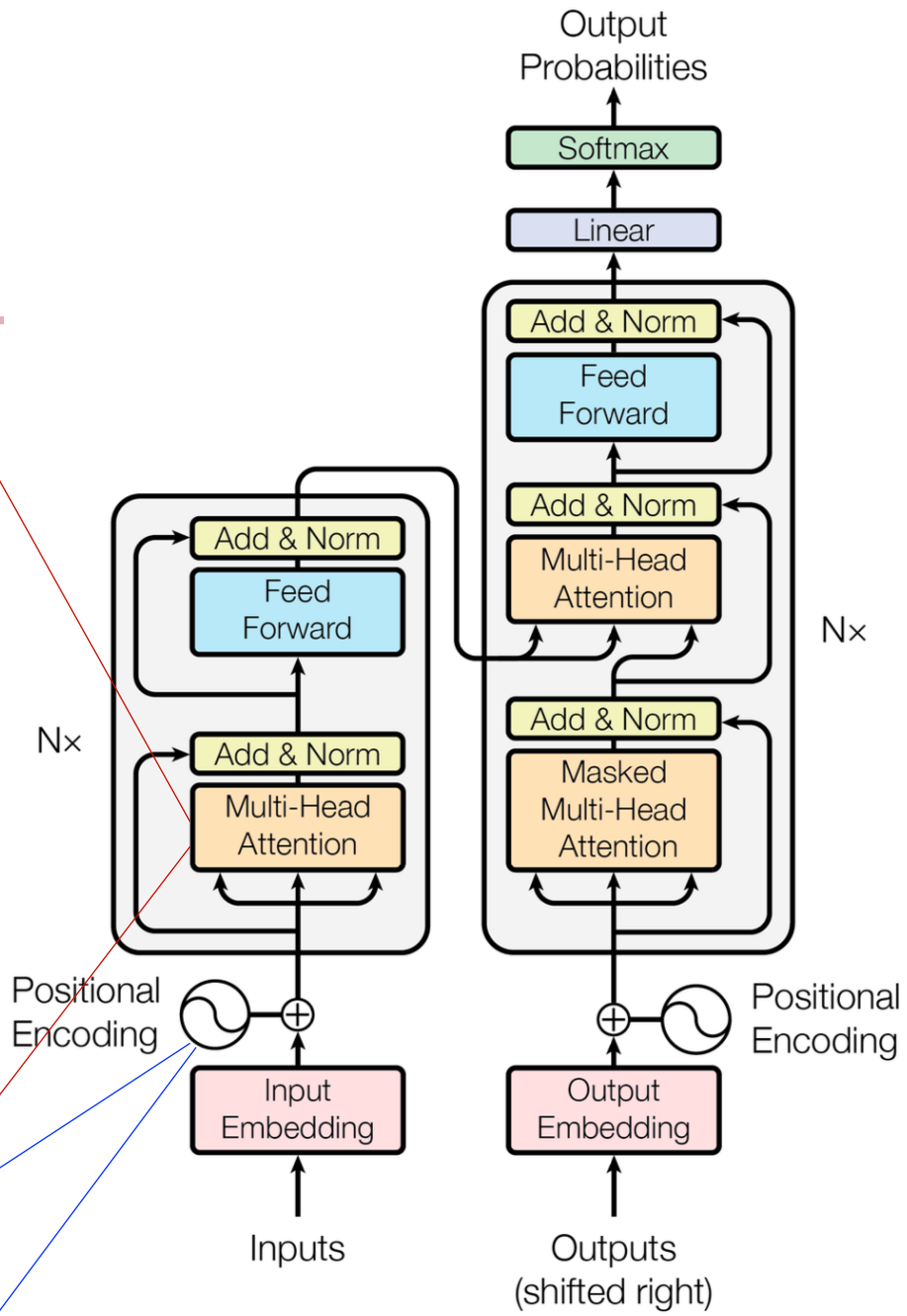
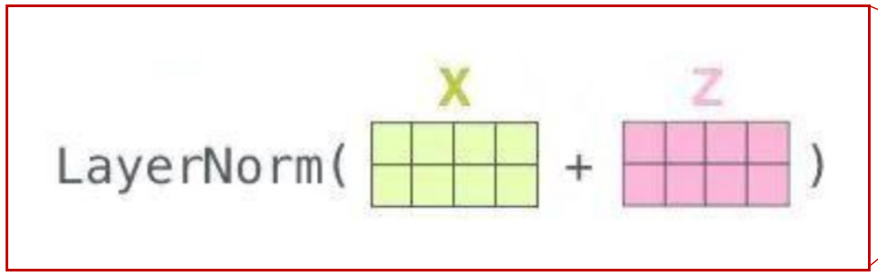
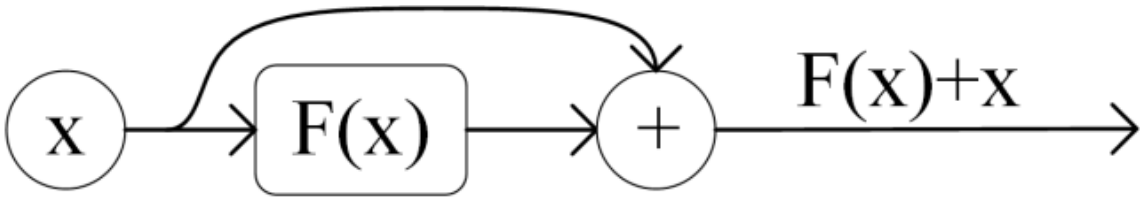


Figure 1: The Transformer - model architecture.

Add

将token原始编码与其
增加注意力后编码相加





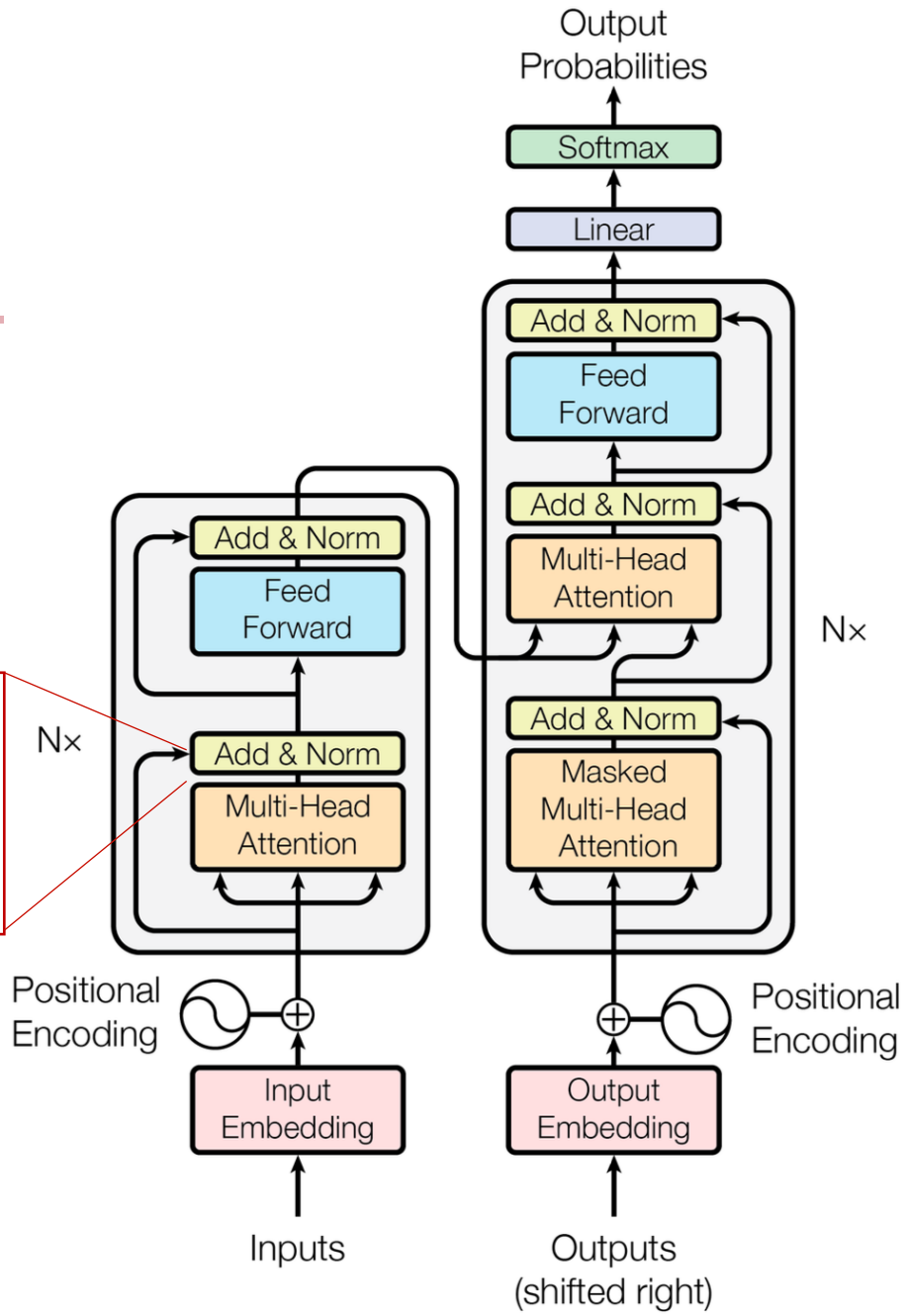
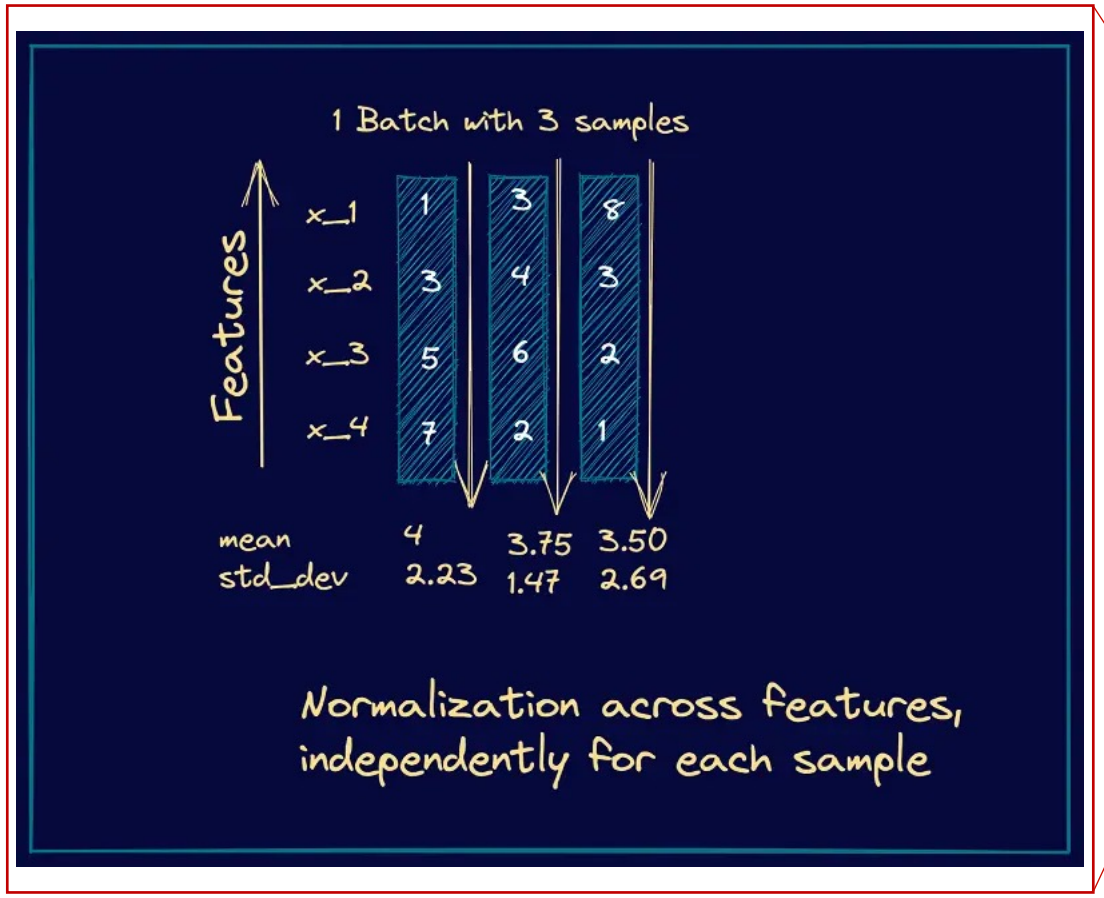


Figure 1: The Transformer - model architecture.

Layer Normalization



https://arxiv.org/abs/1607.06450

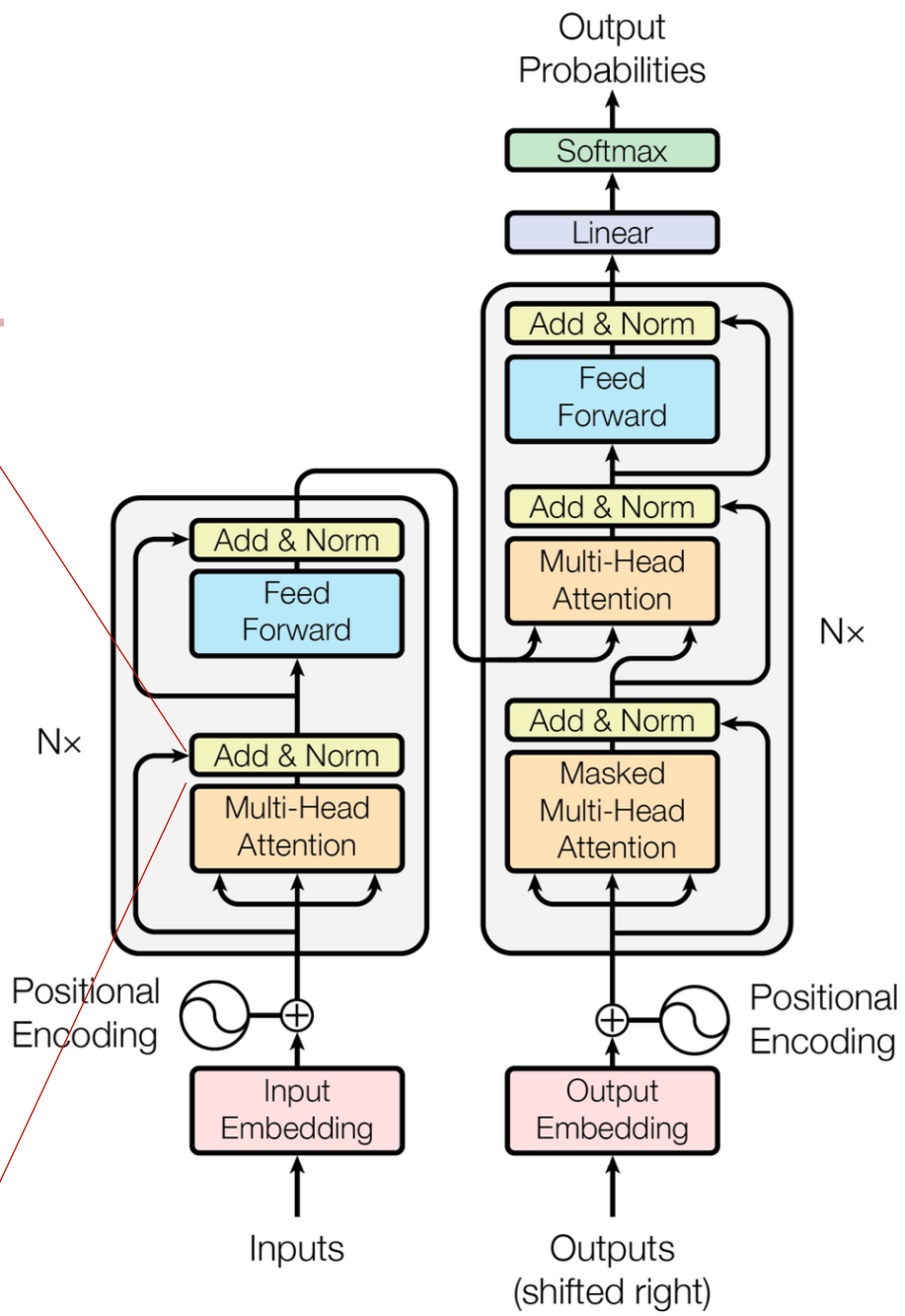
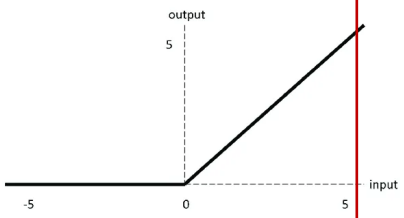


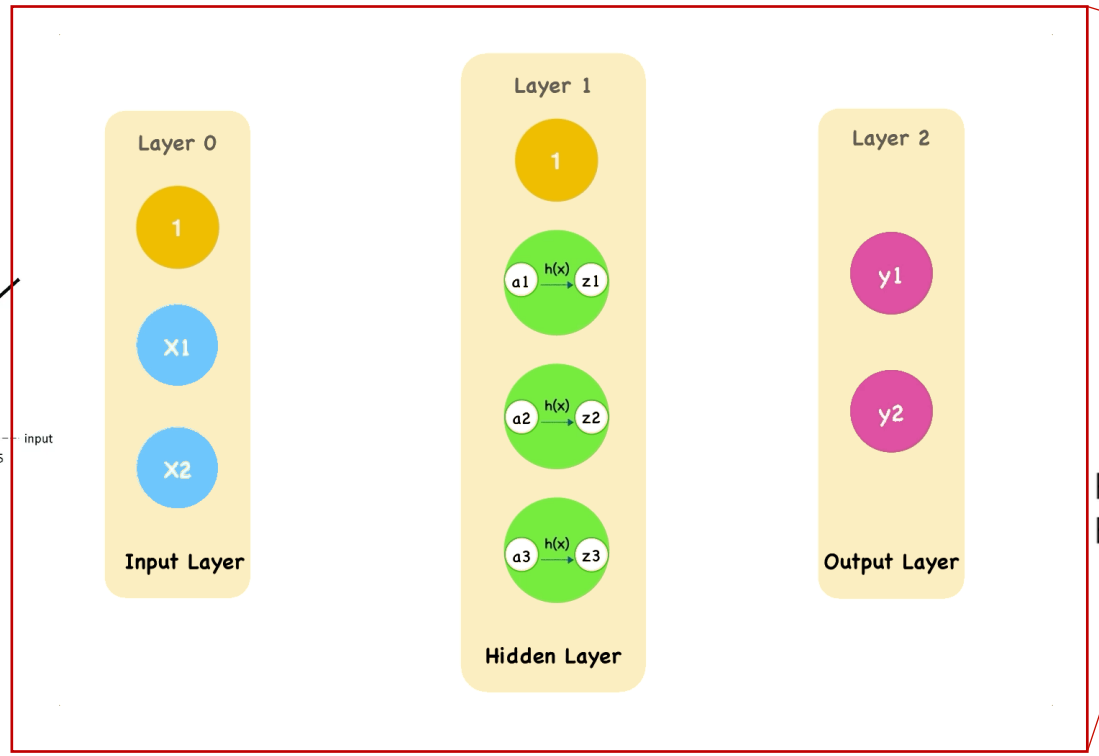
Figure 1: The Transformer - model architecture.

Feed Forward层

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



ReLU激活函数



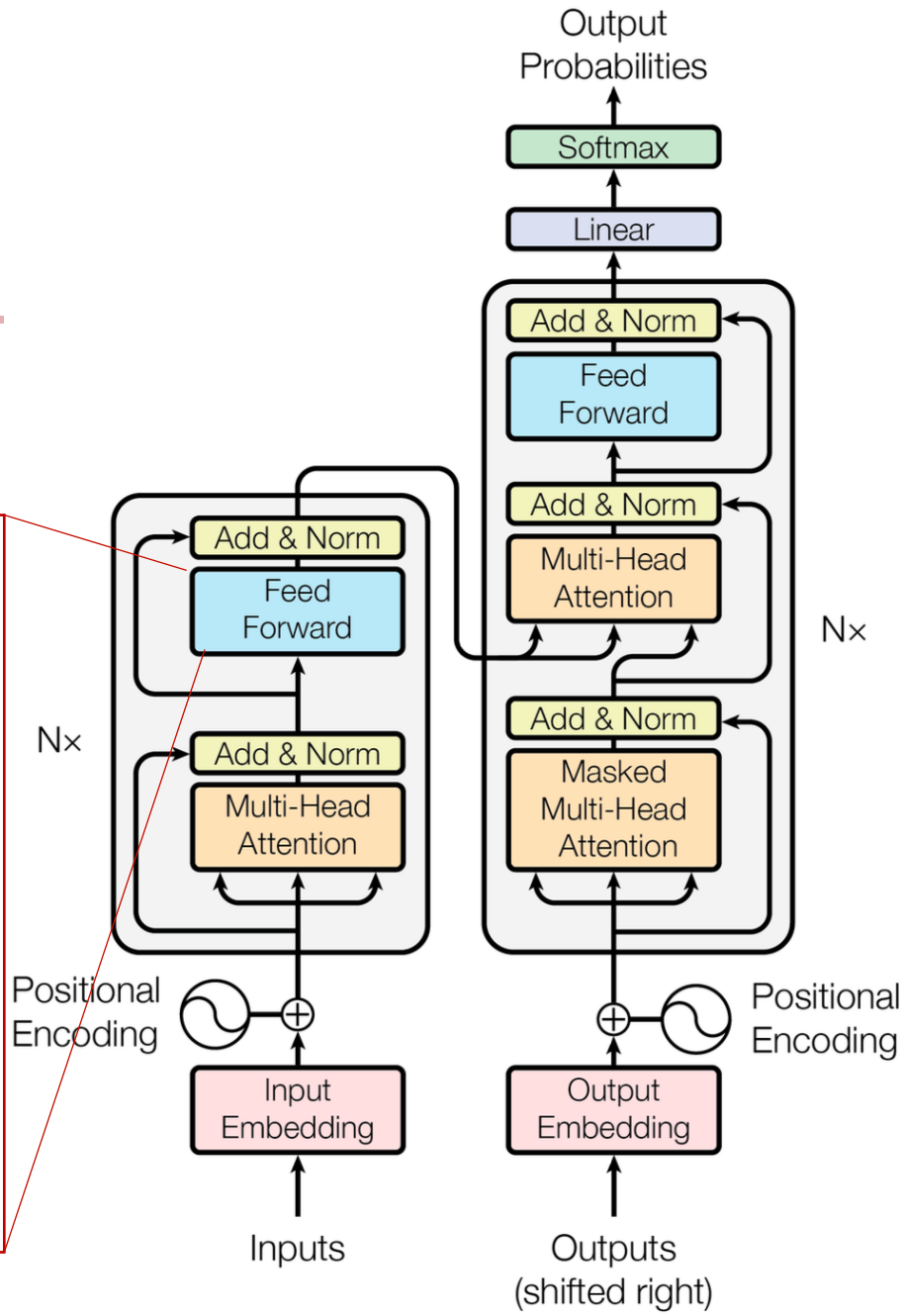
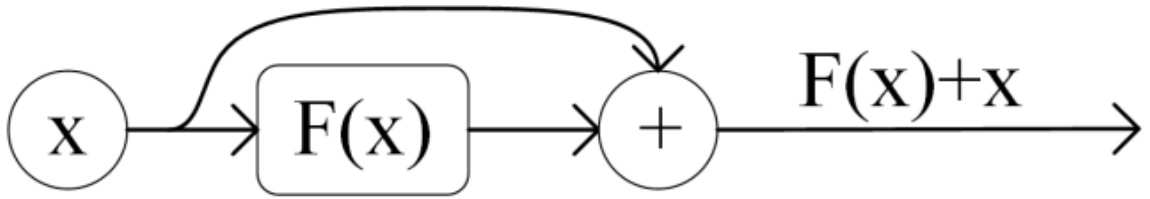


Figure 1: The Transformer - model architecture.

Add&Norm

将token原始编码与经过FFN层后相加

$$\text{LayerNormal}(X + \text{FeedForward}(X)))$$



残差网络

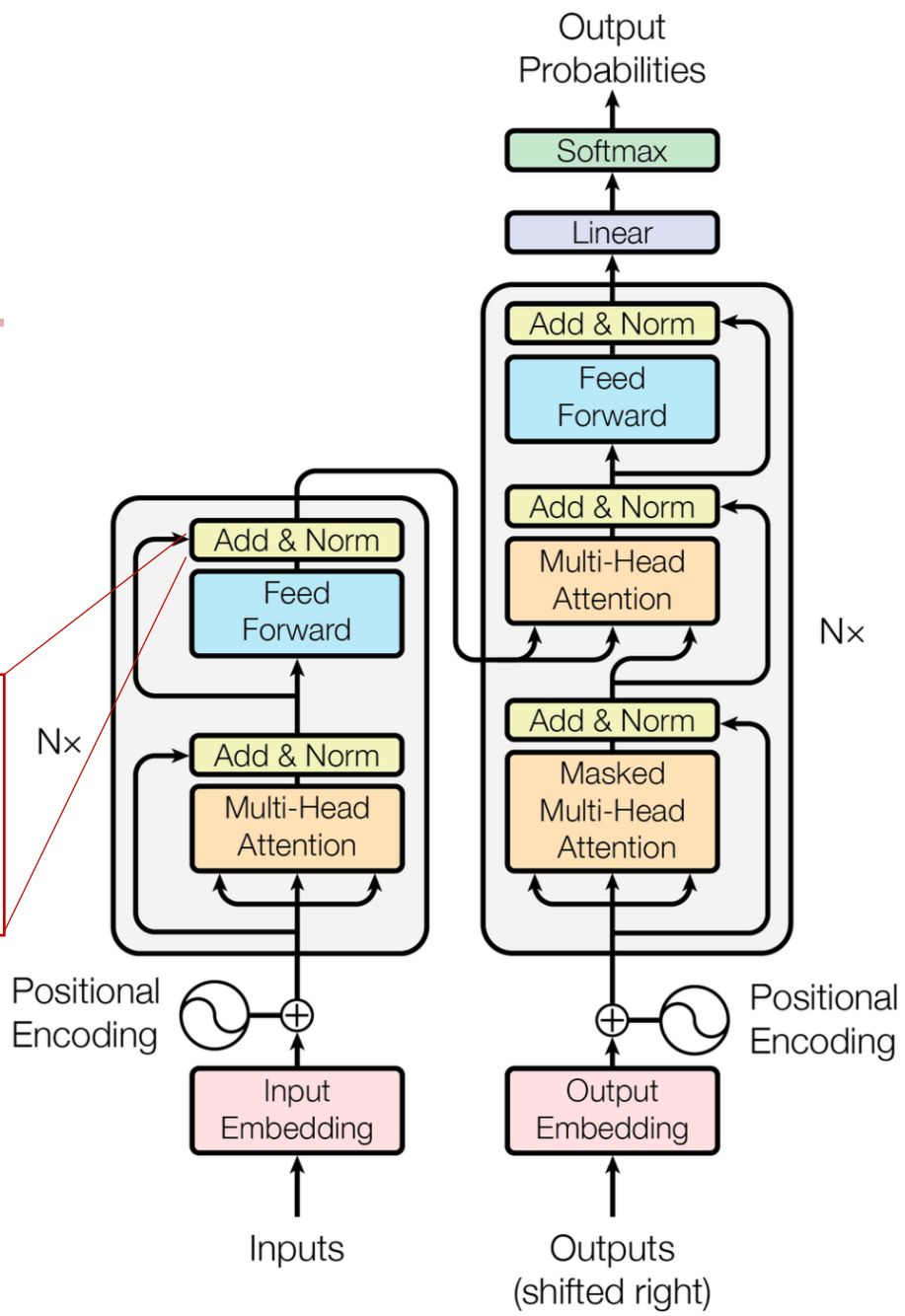


Figure 1: The Transformer - model architecture.

交叉注意力

Q来自解码器，KV来自编码器

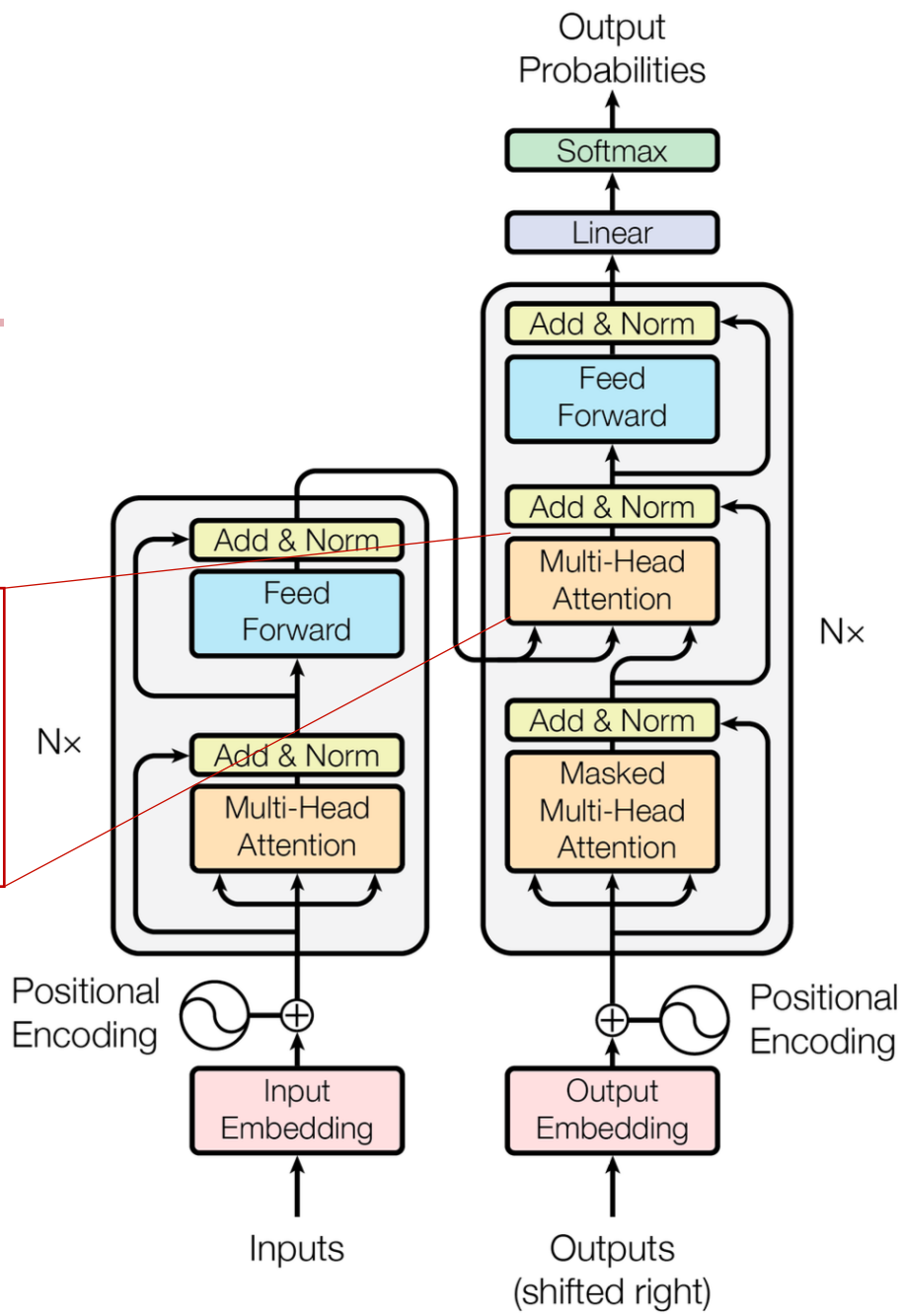
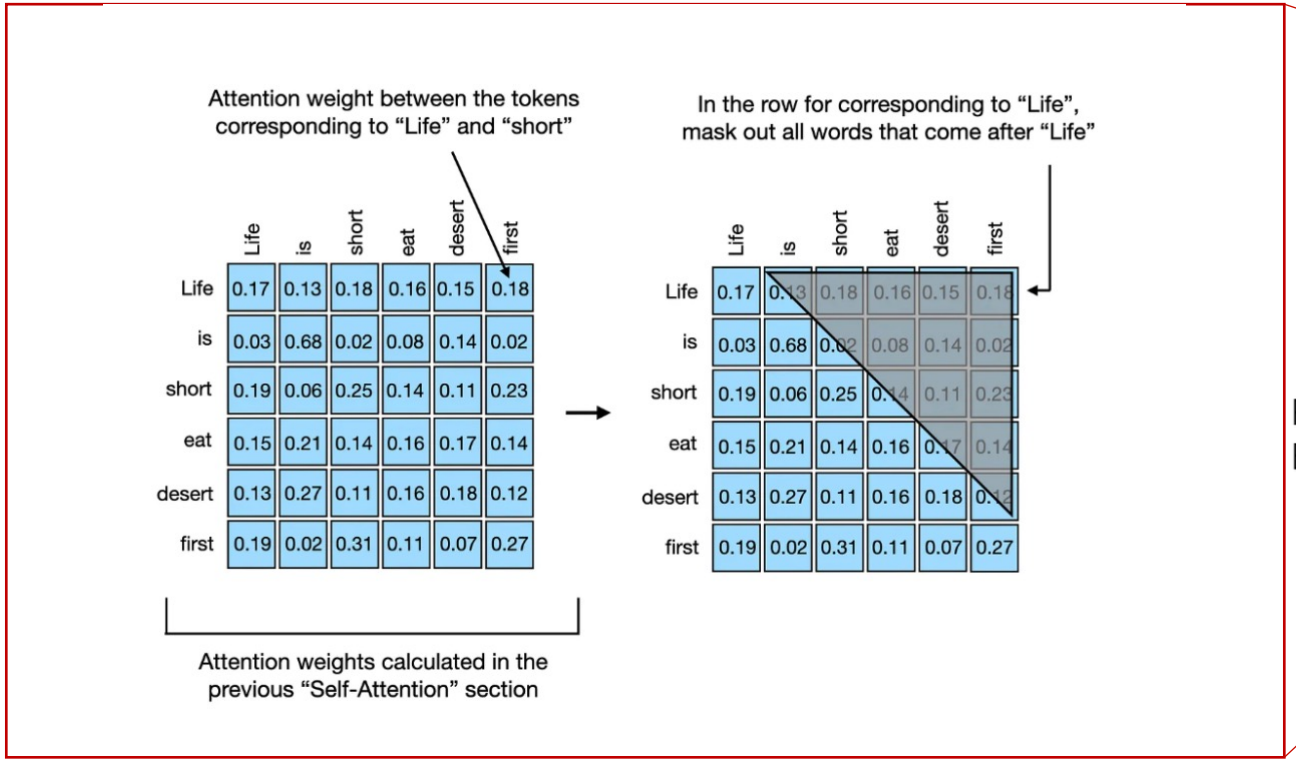


Figure 1: The Transformer - model architecture.

Masked MHA掩码多头注意力

将所有指向未来位置的注意力权重，强行加上一个负无穷大（-∞）的值，人为地设置了只能看左侧信息



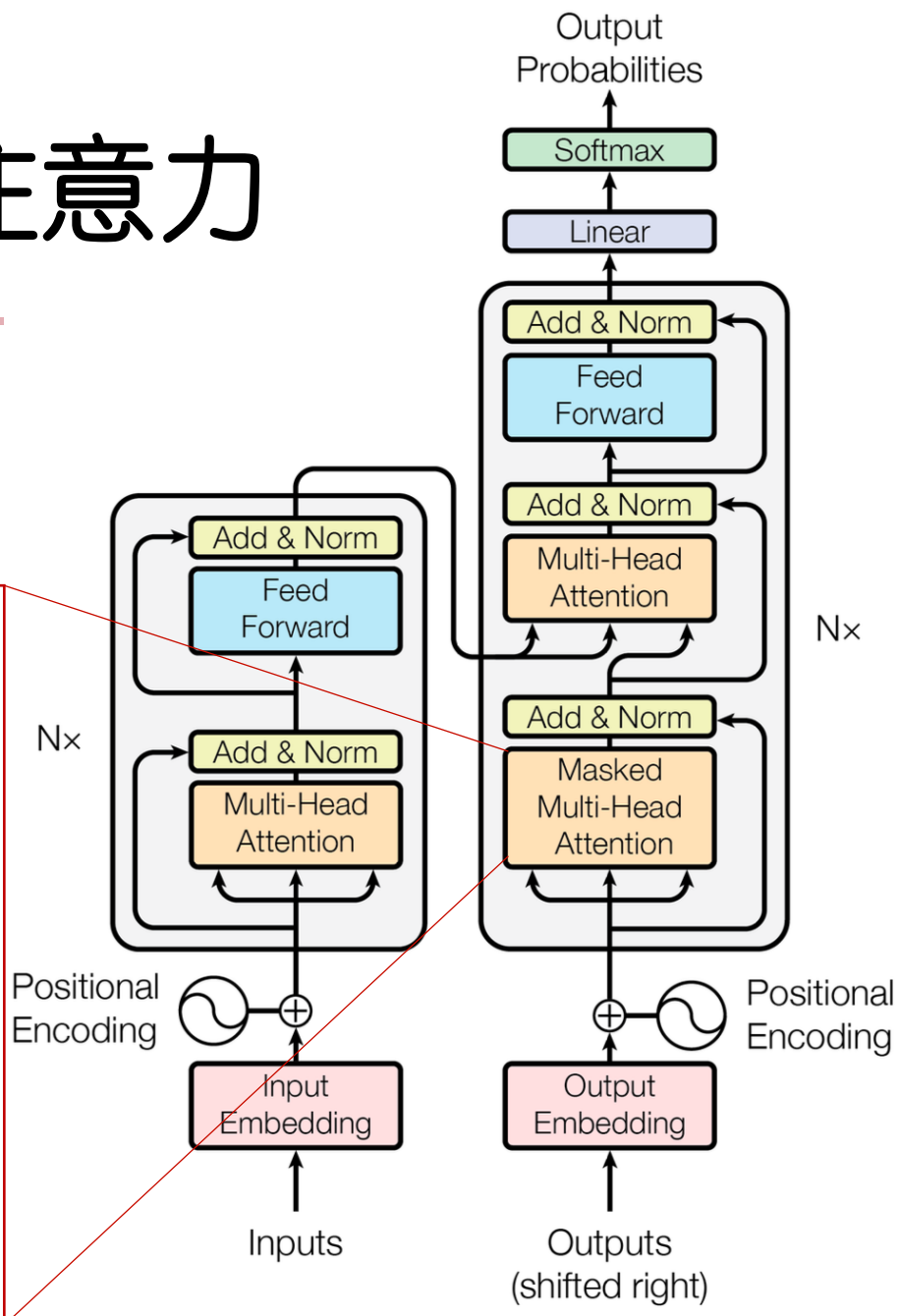
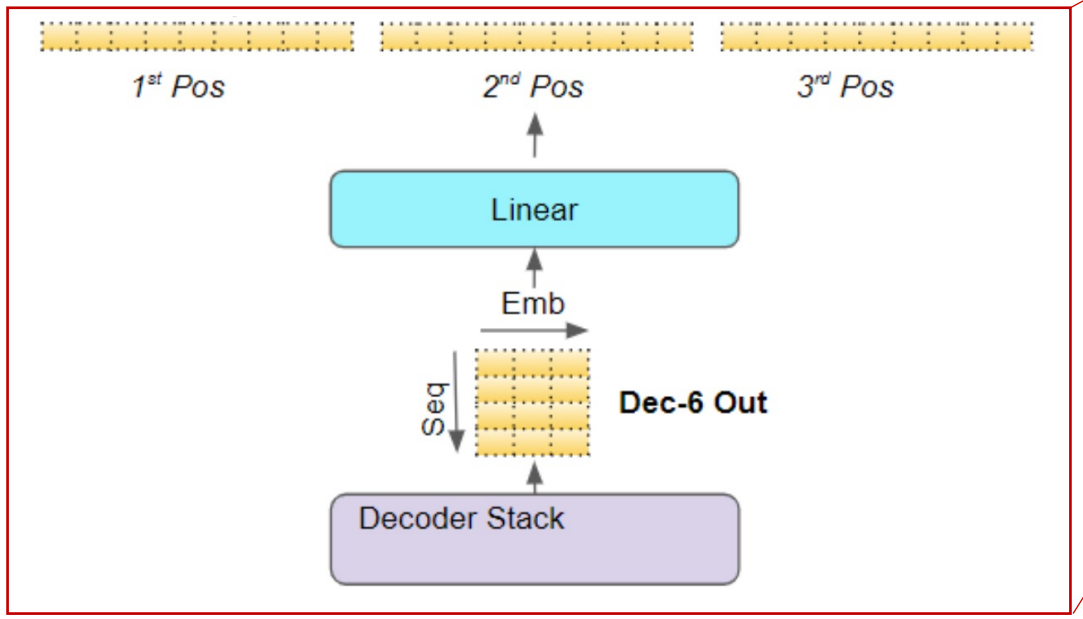


Figure 1: The Transformer - model architecture.

线形层

将注意力值扁平化



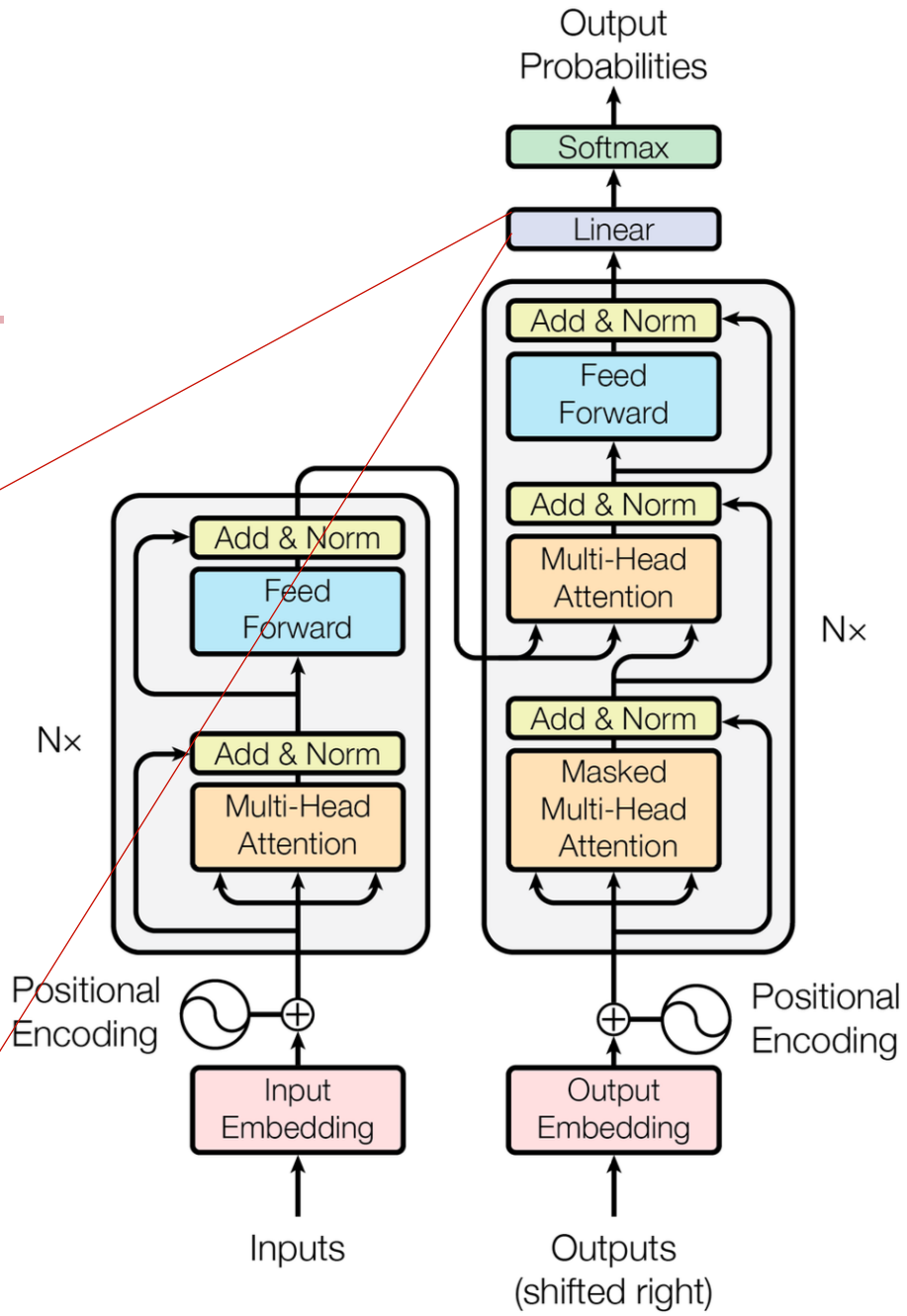
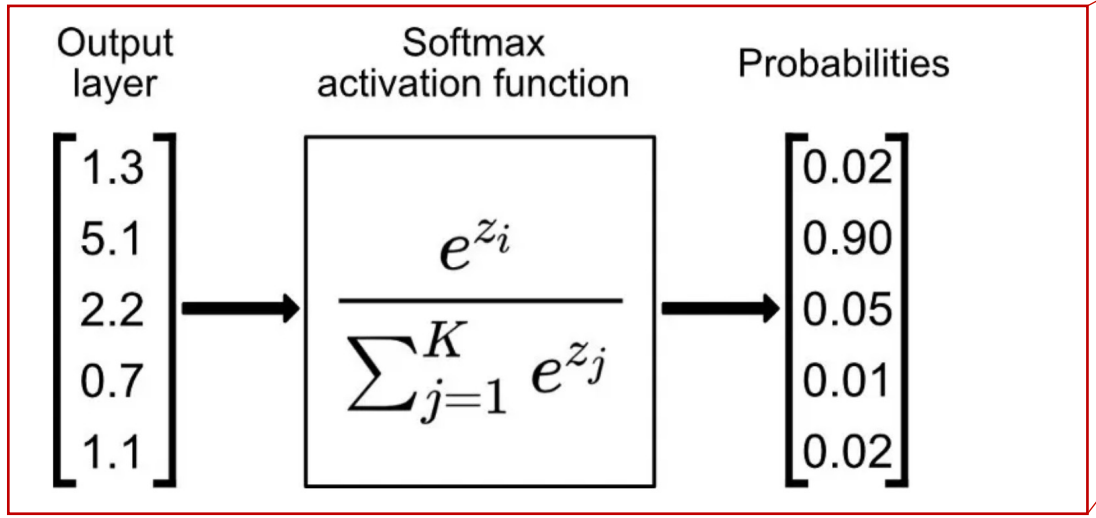


Figure 1: The Transformer - model architecture.

Softmax



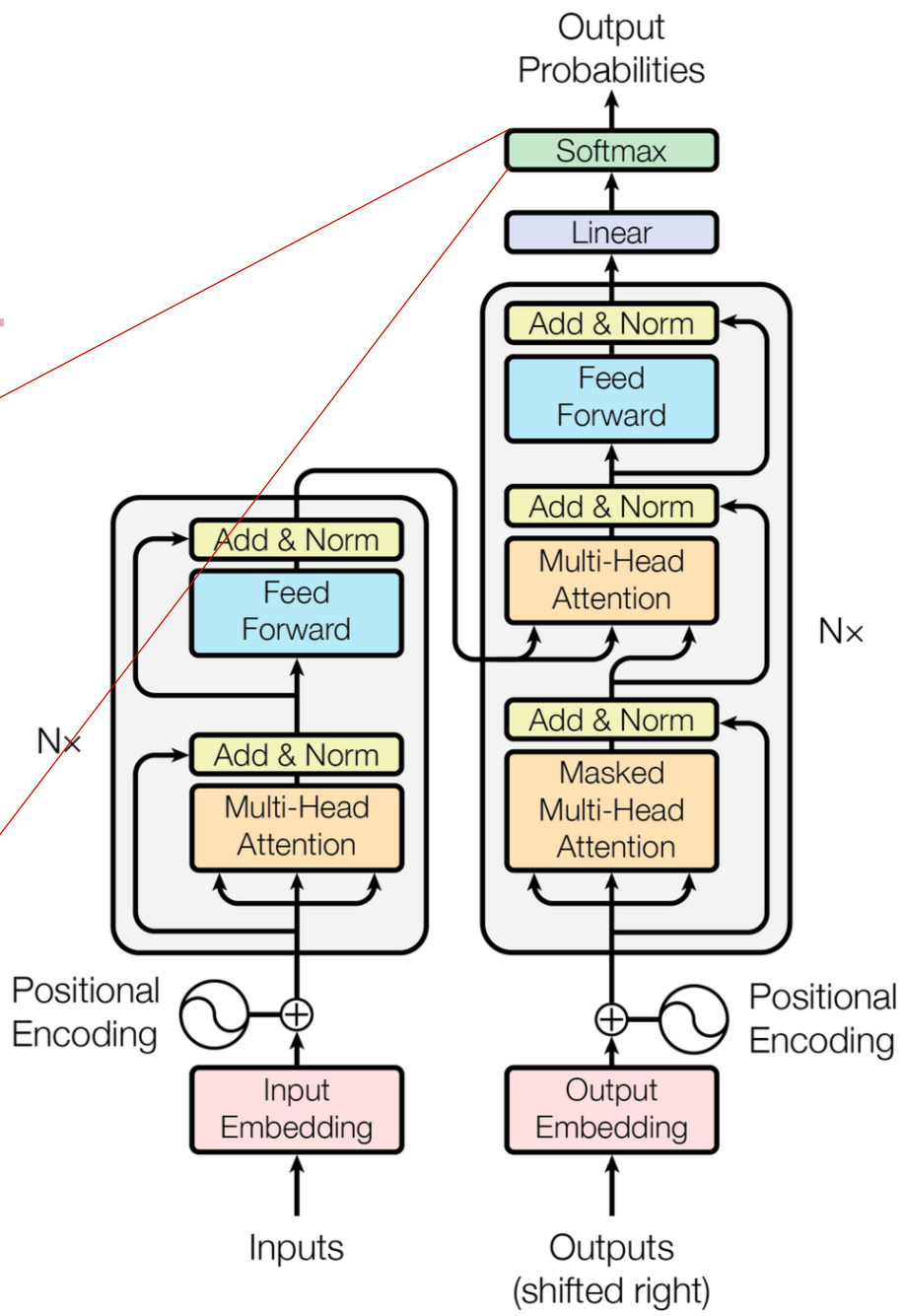
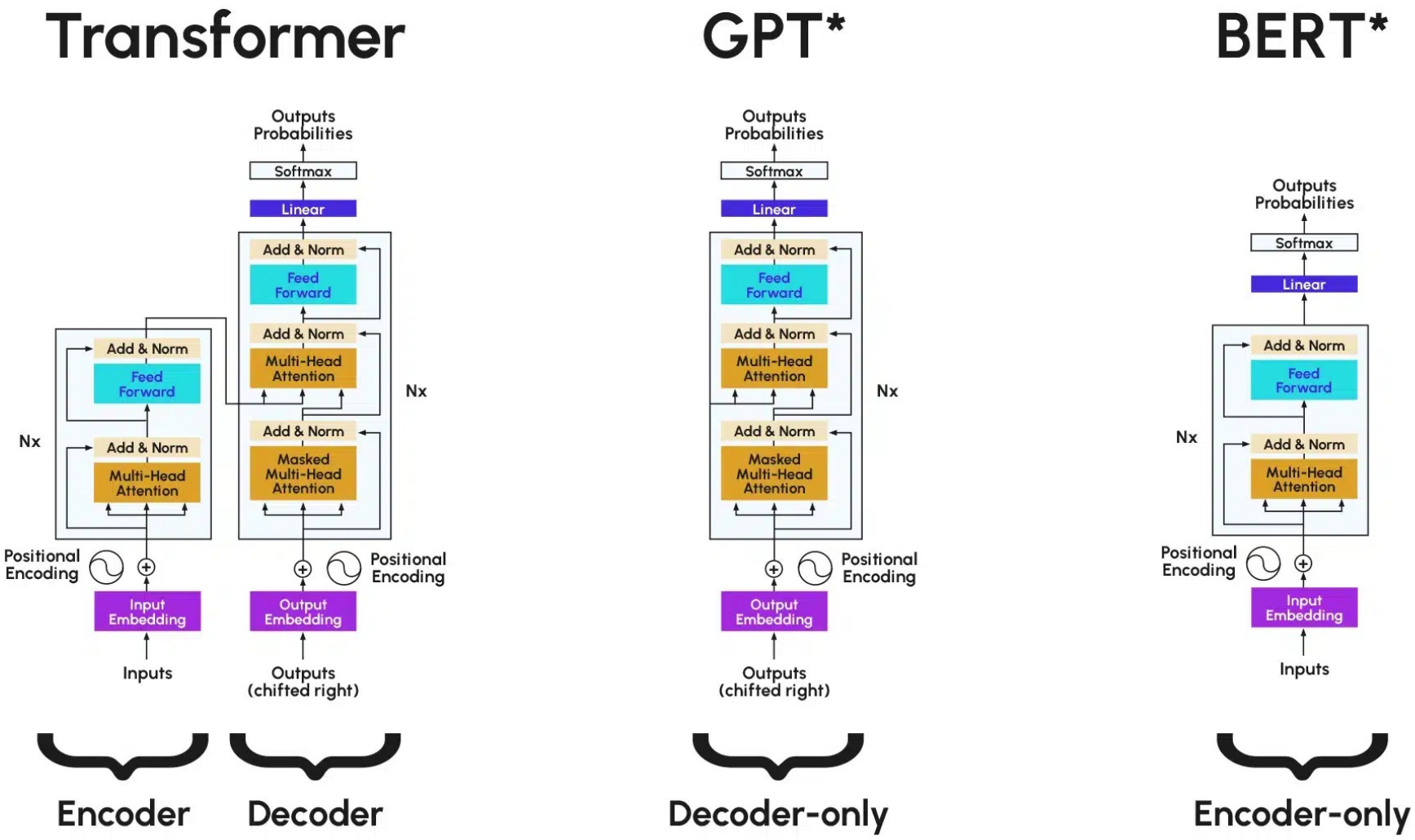
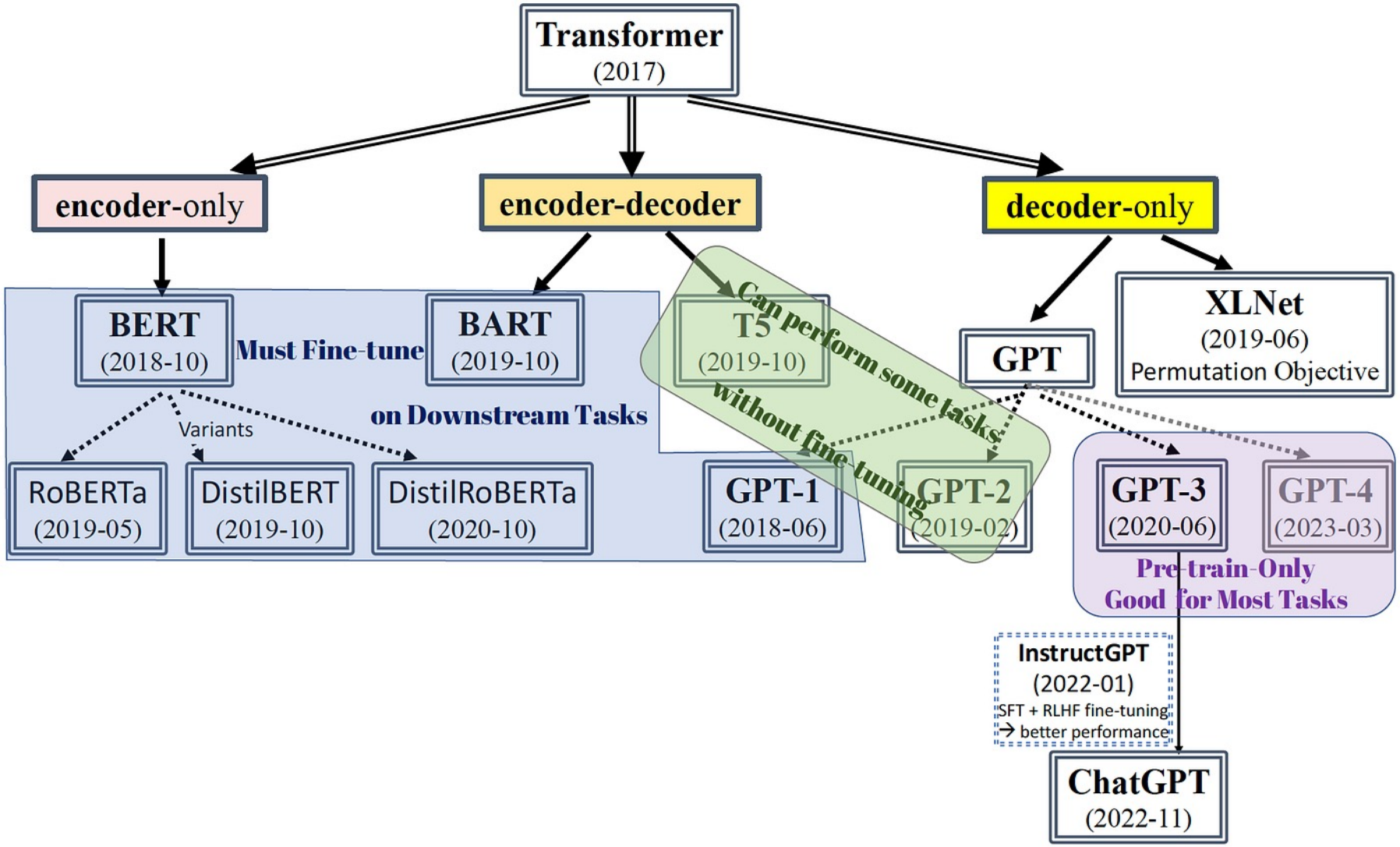


Figure 1: The Transformer - model architecture.

Transformers的变体



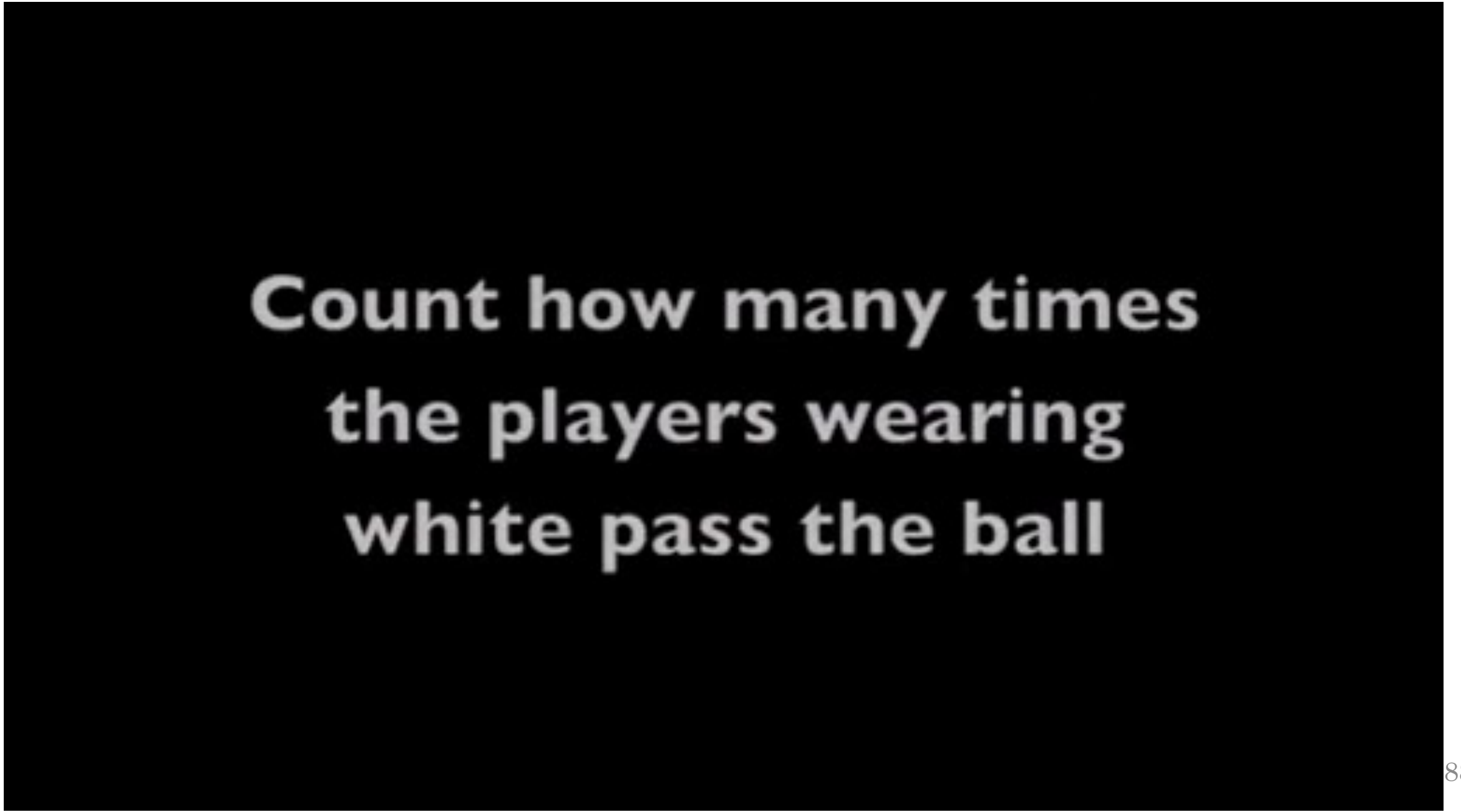
使用Transfomer的模型



本节复习

- Encoder-Decoder中的Attention
- Self-Attention$(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$
- Position Embedding
- Transformer Architecture

测测你的注意力


Count how many times
the players wearing
white pass the ball

参考文献

- Cho, Kyunghyun, et al. "Learning phrase representations using RNN encoder–decoder for statistical machine translation." *EMNLP*. 2014.
- Vaswani, Ashish, et al. "Attention is all you need." *Advances in neural information processing systems* 30 (2017).
- Su, Jianlin, et al. "Roformer: Enhanced transformer with rotary position embedding." Neurocomputing 568 (2024): 127063.

作业

- 阅读“**Attention is all you need**” 论文
  - 写论文+代码的阅读笔记，并在线发布/提交作业
  - 加分题：代码阅读及复现
    - https://github.com/tensorflow/tensor2tensor
  - 完成时间：第**5**周课（**4月3号**）前

致 谢

- 胡玥、曹亚男、方芳：国科大《自然语言处理基础》
- 曹亚男、任昱冰：国科大《深度学习与自然语言处理概述》


THANKS
https://ictkc.github.io/teaching/2026spring-nlp