RNN条件生成与Attention

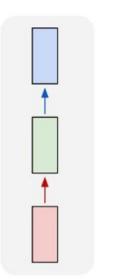
七月在线 张雨石 2018年9月13日 http://blog.csdn.net/stdcoutzyx

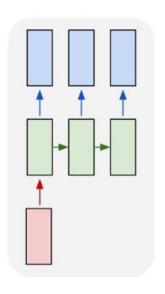
RNN条件生成与Attention

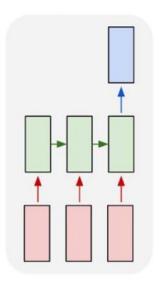
- □ RNN条件生成
- □机器翻译
- ☐ Attention
- □ 图像生成文本

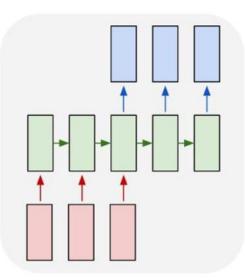
RNN条件生成

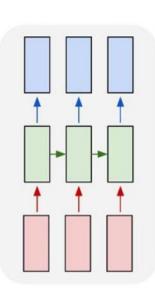
□ RNN解决的问题











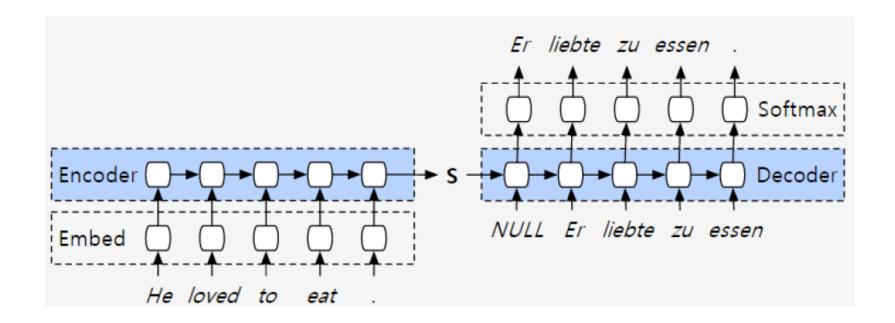
RNN条件生成

- □ RNN解决的问题
 - 图片生成描述
 - 文本分类
 - ■机器翻译
 - 视频解说
- □ 条件生成问题 P(y|x)

机器翻译

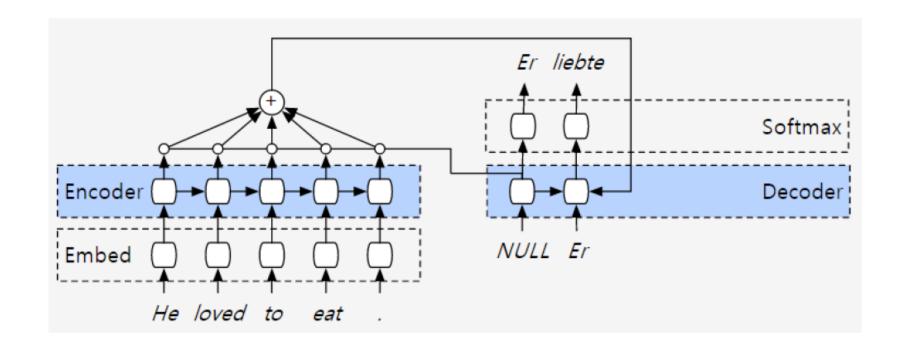
- □ V1: Encoder-Decoder
- ☐ V2: Attention-based Encoder-Decoder
- □ V3: Bi-directional encode layer
- ☐ V4: Residual-based Encoder-Decoder
- □总结

V1: Encoder-Decoder

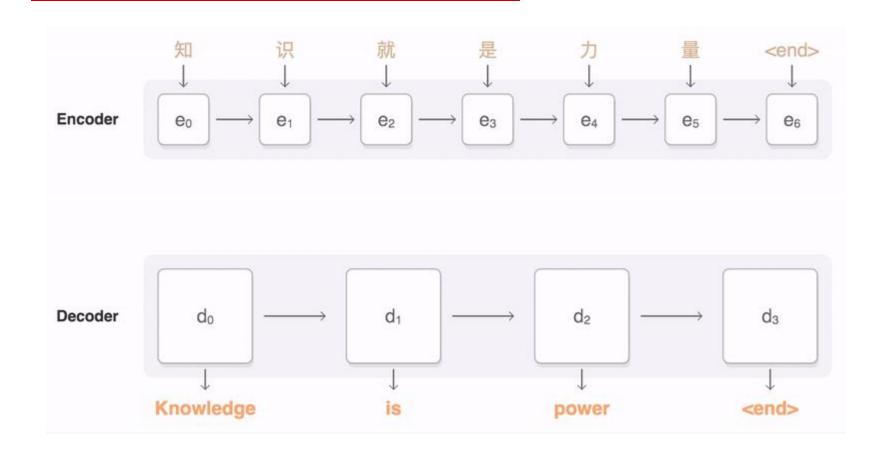


V1: Encoder-Decoder

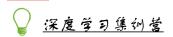
- □ 编码过程
- □ 解码过程
- □缺点
 - 定长编码是信息瓶颈
 - 长度越长,前面输入进RNN的信息就越被稀释



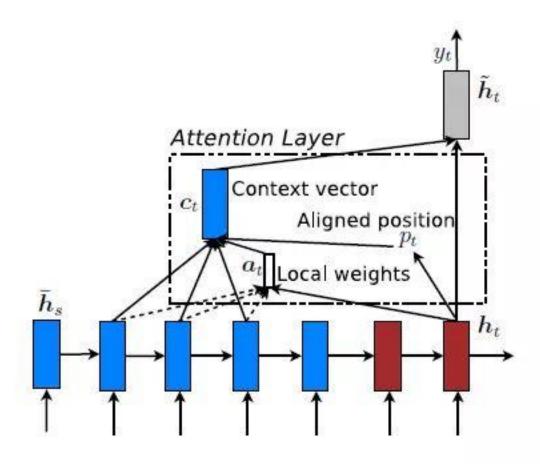
- □ Attention 层
 - Attention 计算
 - □ LSTM各步的输出向量a=[a1,a2,...,an]
 - □ Decoder每步的中间状态hi
 - \square Alpha = [tanh(w1*aj + w2*hi) for j in range(n)]
 - Attention か权
 - ☐ Alpha * a

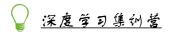


☐ Global Attention ■ 计算量大 h_t Attention Layer Context vector c_t Global align weights

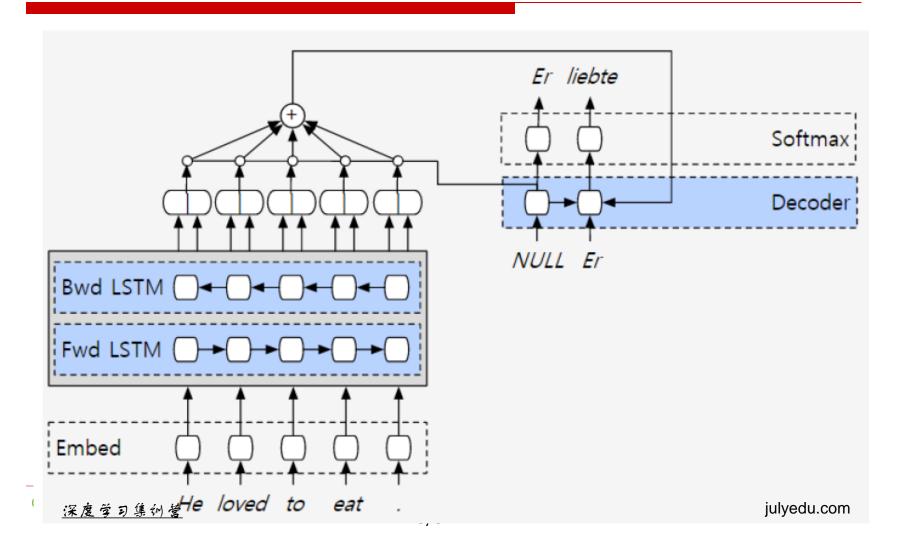


☐ Local Attention

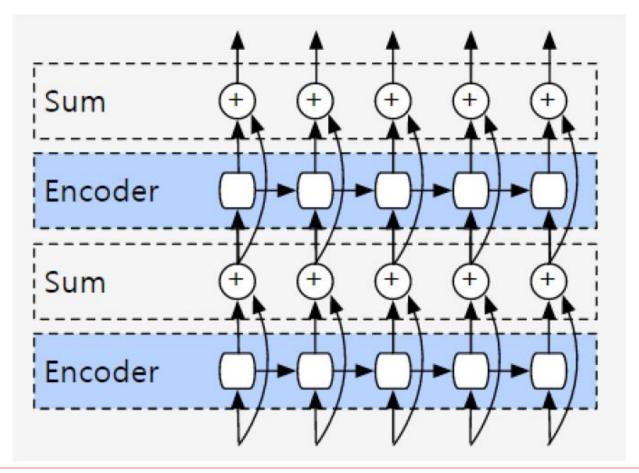




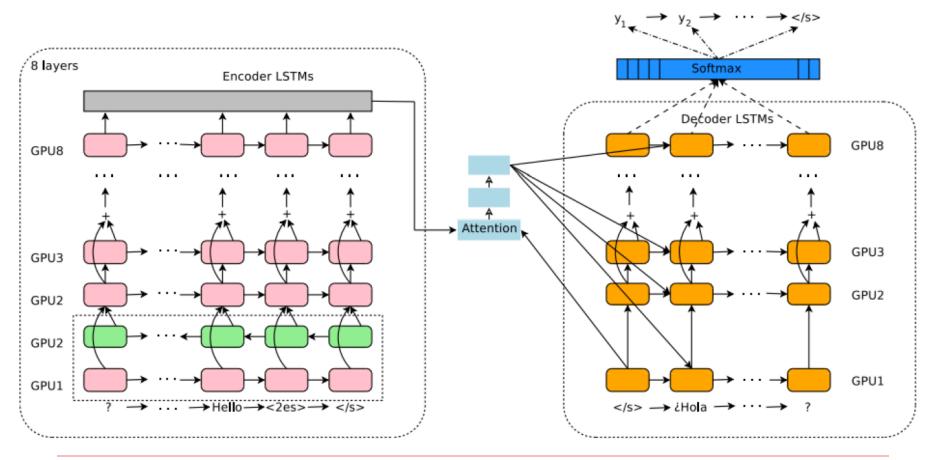
V3: Bi-Directional Encode layer



V4: Residual Encode layer



机器翻译-总结



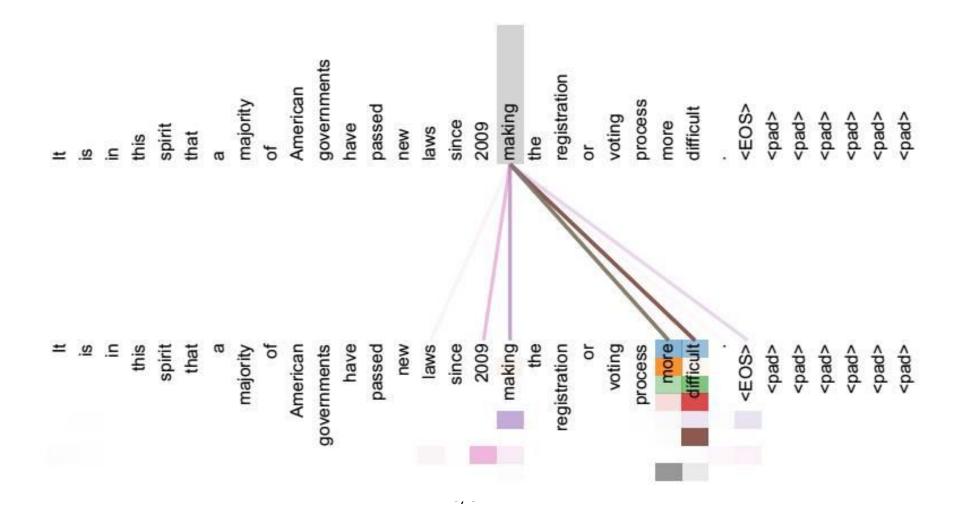
Attention

- ☐ Global Attention
- ☐ Local Attention
- ☐ Self Attention
- ☐ Hierarchical Attention

Self Attention

- □ 传统的attention只有source和target之间的关 联关系
- □ 忽略了source和target端分别的关联关系

Self Attention

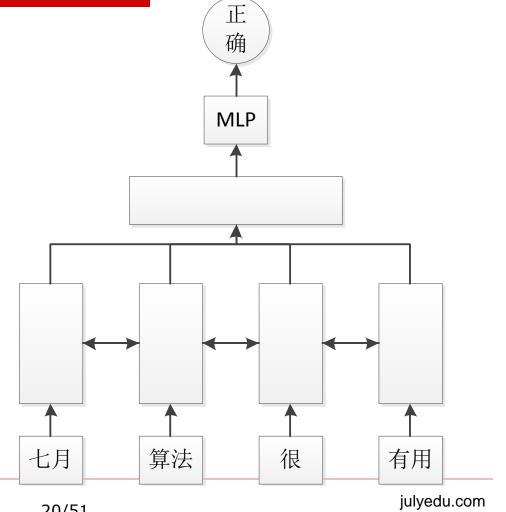


Self Attention

- □ 可以理解为source=target的encoder-decoder
- □ 捕捉到词与词之间的关系
- □ 增加并行性

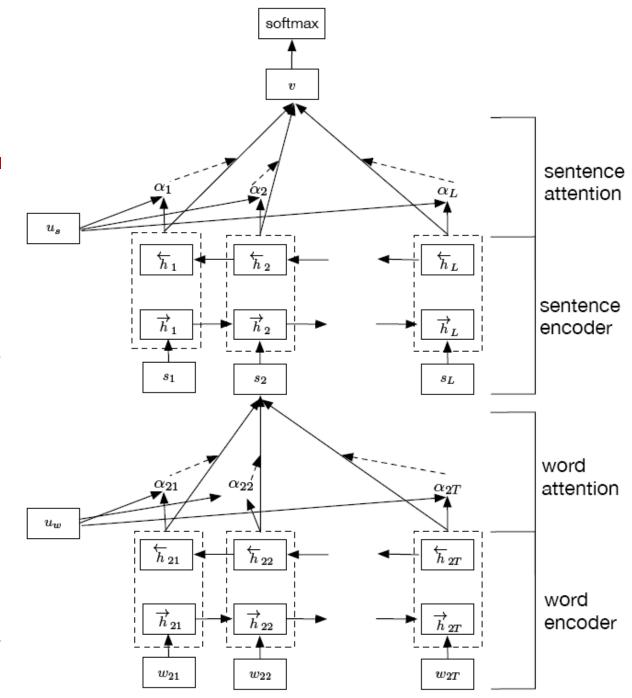
Hierarchical Attention

- □ 文本分类
 - 双向LSTM
 - 输出合并
 - □ 拼接
 - ☐ Average
 - max



Hierarchical

- □ 文本分类
 - 分层
 - □ 词到句
 - □句到段落
 - Attention





图像生成文本

- □问题引入
- □模型变迁
 - M-RNN
 - Neural Image Caption
 - Attention-based

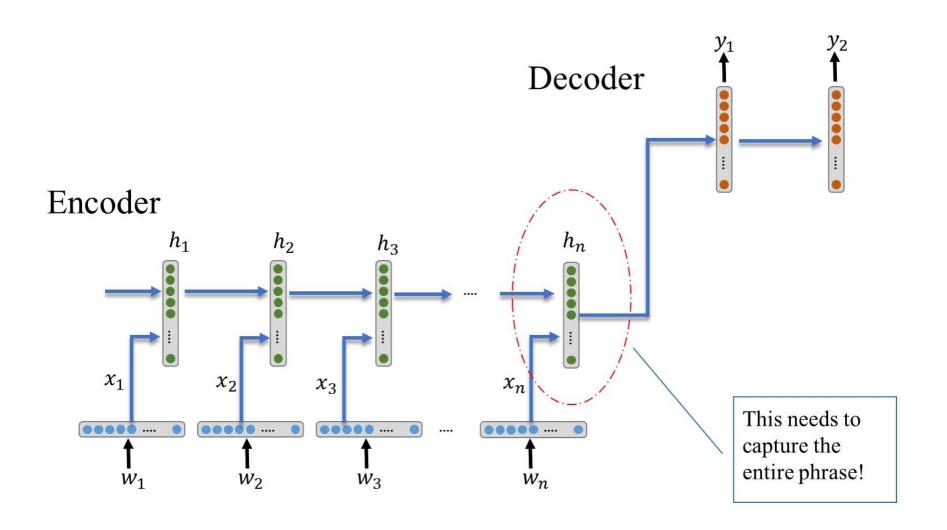
- □ Deep Learning出现之前
 - 检索问题
 - 不能泛化到新的数据

- □图像搜索
 - 找到图像对应的描述,丰富搜索元数据
- □ 盲人导航
- □ 少儿教育
 - 看图说话

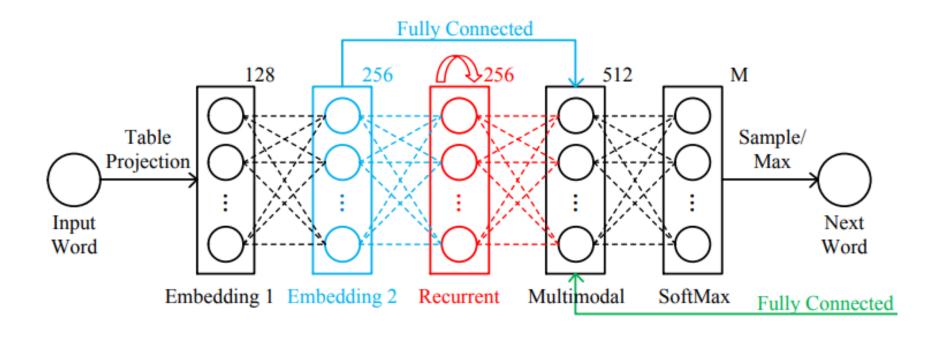
- □数据集
 - IAPR TC-12: 20000张图像, 平均每张图像有1.7 句描述
 - Flickr8k: 8000张图像, 语法比IAPR简单
 - Flickr30k: 31783张图像, 158915句描述, 平均每个五句。
 - MS COCO: 16W张图像
 - AI Challenger: 图像中文描述数据

- □ 评测
 - BLEU score
 - 句子检索和图像检索

模型变迁—Encoder-Decoder



模型变迁——Multi-model RNN

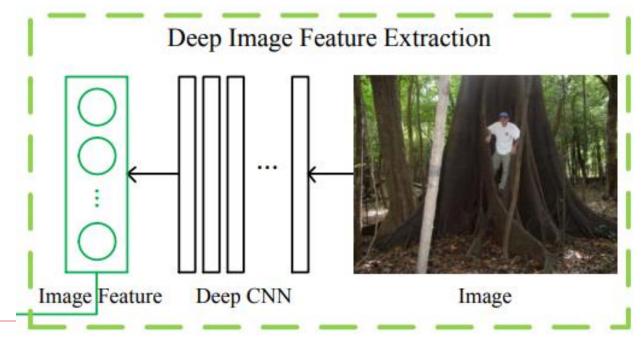


模型变迁——Multi-Model RNN

- □ 输入词生成embedding
- □ Embedding输入到RNN和Multi-Model
- □ RNN生成更加抽象的embedding
- □ 原始Embedding、RNN的embedding和图像 Feature同时输入给分类层

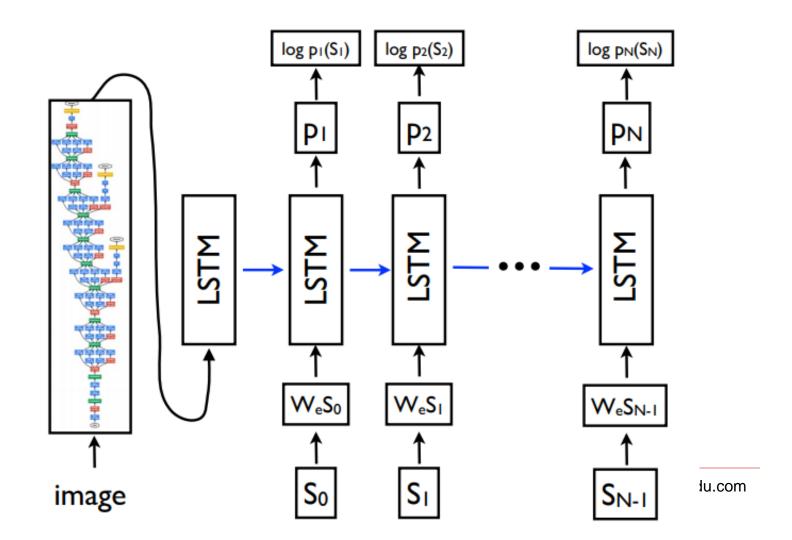
模型变迁——Multi-model RNN

- ☐ AlextNet 7th feature
- ☐ Object detection feature



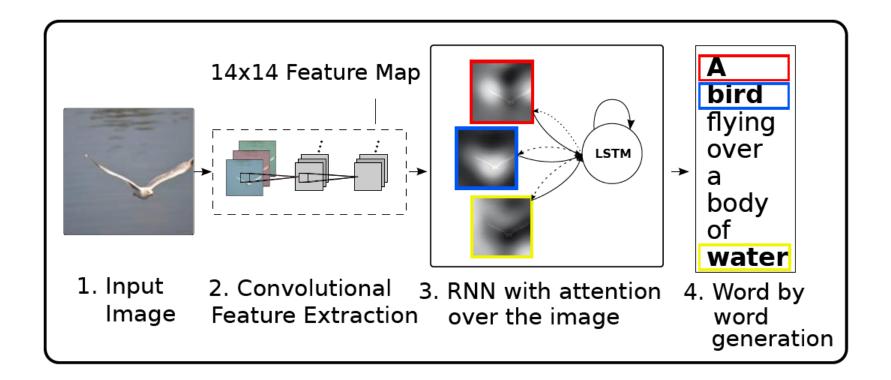
模型变迁——Show And Tell

深人



模型变迁——Show And Tell

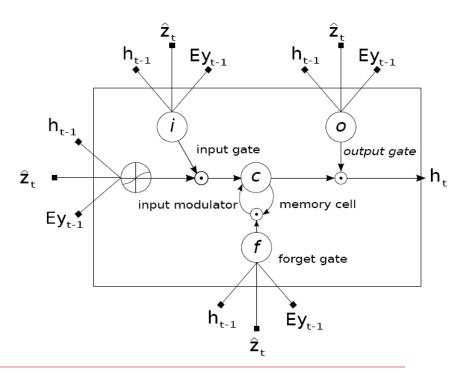
- □ 图像特征使用更强大的CNN提取
 - GoogNet、Residual等
- □ 图像特征只提取一次
- □ LSTM生成文本



□不使用全连接层而是某个卷积层的feature

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- 不使用全连接层
- 使用卷积层的输出
 - □ 有位置信息
- LSTM输入是加权和
 - attention



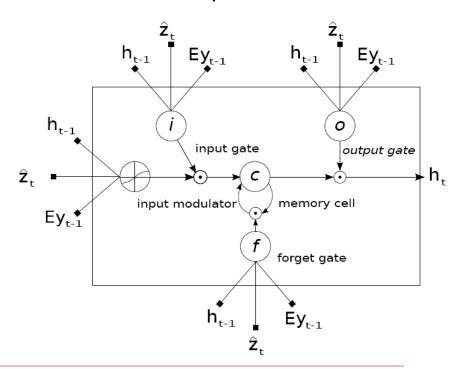
- □不使用全连接层而是某个卷积层的feature
 - 14*14*256: 有14*14个位置可以选择

$$a = \{\mathbf{a}_1, \dots, \mathbf{a}_L\}, \ \mathbf{a}_i \in \mathbb{R}^D$$

$$e_{ti} = f_{\text{att}}(\mathbf{a}_i, \mathbf{h}_{t-1})$$

$$\alpha_{ti} = \frac{\exp(e_{ti})}{\sum_{k=1}^{L} \exp(e_{tk})}$$

$$\hat{\mathbf{z}}_t = \phi\left(\left\{\mathbf{a}_i\right\}, \left\{\alpha_i\right\}\right)$$





A woman is throwing a frisbee in a park.



A dog is standing on a hardwood floor.



A <u>stop</u> sign is on a road with a mountain in the background.



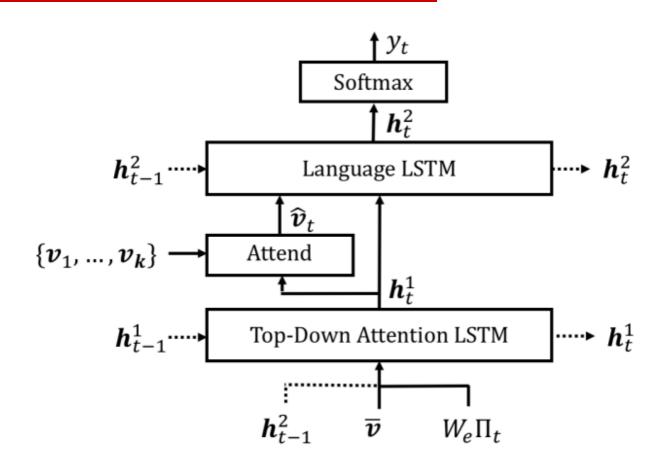
A little <u>girl</u> sitting on a bed with a teddy bear.



A group of <u>people</u> sitting on a boat in the water.

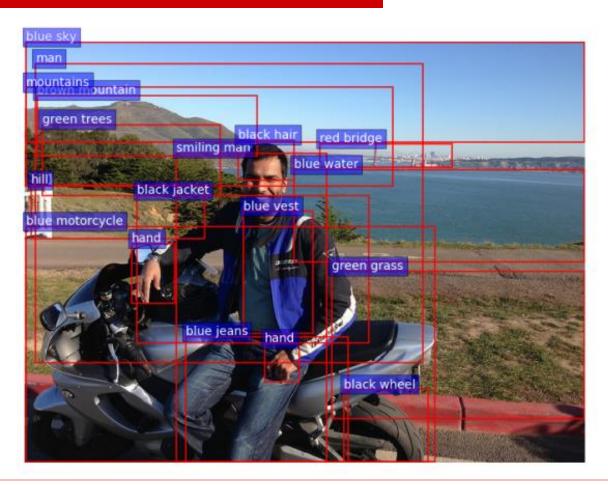


A giraffe standing in a forest with trees in the background.



- □ 第一层LSTM负责学习attention
 - 前一时刻Language Model的hidden state
 - 图像的全局信息
 - □ 所有feature map的平均
 - 输入词语的embedding

$$m{x}_t^1 = [m{h}_{t-1}^2, ar{m{v}}, W_e \Pi_t]$$



□ 第一层LSTM输出和图像feature计算attention

$$a_{i,t} = \boldsymbol{w}_a^T \tanh (W_{va} \boldsymbol{v}_i + W_{ha} \boldsymbol{h}_t^1)$$

$$\boldsymbol{\alpha}_t = \operatorname{softmax} (\boldsymbol{a}_t)$$

$$\hat{\boldsymbol{v}}_t = \sum_{i=1}^K \alpha_{i,t} \boldsymbol{v}_i$$

- □ 第二层LSTM
 - 第一层LSTM的隐含层
 - 加权平均的图像feature

$$oldsymbol{x}_t^2 = [\hat{oldsymbol{v}}_t, oldsymbol{h}_t^1]$$

$$p(y_t \mid y_{1:t-1}) = \operatorname{softmax} (W_p \boldsymbol{h}_t^2 + \boldsymbol{b}_p)$$

总结

- □ RNN条件生成问题
- □机器翻译
 - Encoder-Decoder、attention、双向、残差
- ☐ Attention
 - Self-attention、Hierarchical attention
- □ 图像生成文本
 - Multi-Modal. Show and Tell
 - Show attend and tell. Top-down bottom-up attention

Thanks!

Q&A