



# 语言与视觉多模态智能的进展

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# 提纲



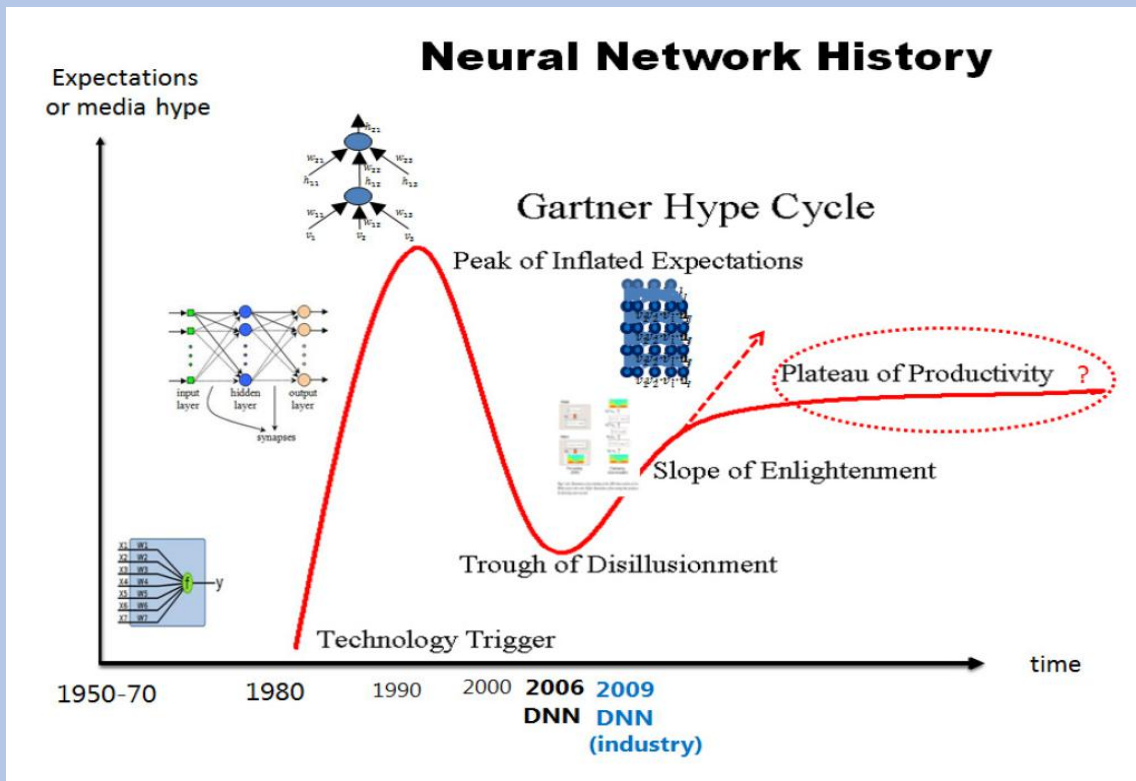
- 近来的一些进展

- 深度学习
- 语音和自然语言理解

- 语言+视觉多模态智能

- 图像描述 (Image-to-text Captioning)
- 视觉问答 (Visual Question Answering)
- 基于文字描述合成图像 (Text-to-image Synthesis)

# 深度学习的发展



Geoff Hinton



Yoshua Bengio



Yann LeCun

# 从学术界到工业界: Scale up!



NIPS08 workshop  
邀请Hinton来做报  
告并探讨与工业界  
合作

## NIPS 2008 WORKSHOP

### Speech and Language: Learning-based Methods and Systems

Organizer: Xiaodong He and Li Deng

Friday, December 12, 2008  
Whistler, British Columbia, Canada

#### INVITED TALKS

New Multi-Level Models for High-dimensional Sequential  
Data

**Geoffrey Hinton, University of Toronto**



Abstract:

I will describe recent developments in learning algorithms for multilevel nonlinear generative models of sequential data. The models are learned greedily, one layer of features at a time and each additional layer of nonlinear features improves the overall generative model of the data. In earlier work (Taylor et. al. 2006) the basic

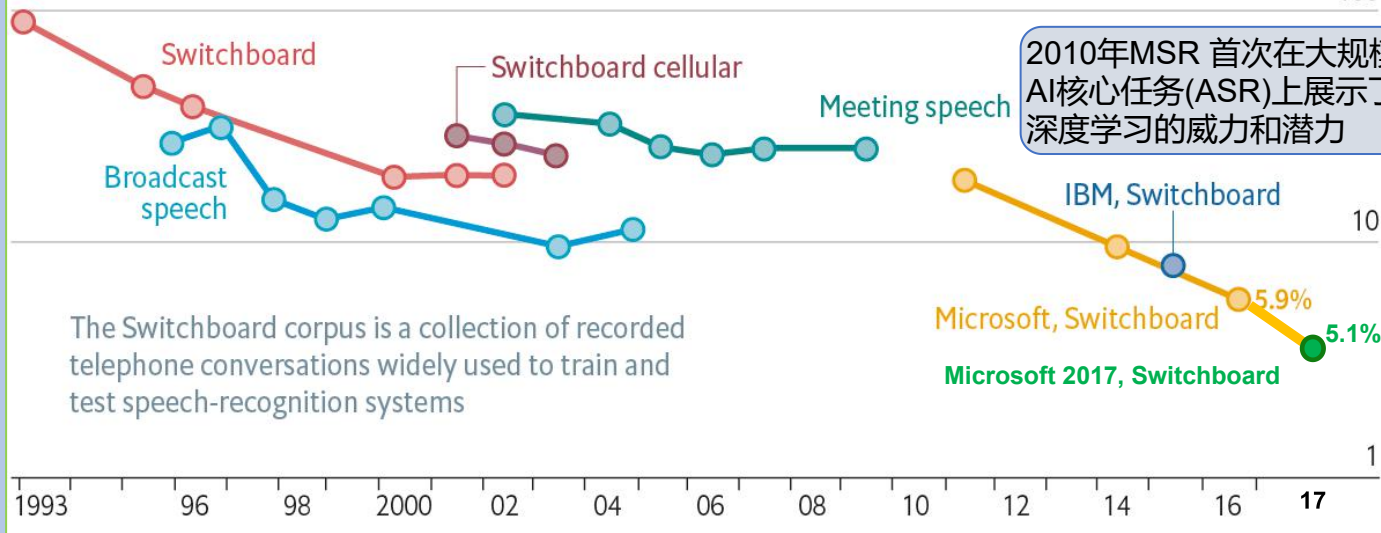


## 在标准测试上精度达到人类水平!

### Loud and clear

Speech-recognition word-error rate, selected benchmarks, %

Log scale  
100



2010年MSR 首次在大规模AI核心任务(ASR)上展示了深度学习的威力和潜力

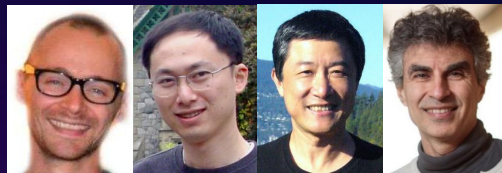
The Switchboard corpus is a collection of recorded telephone conversations widely used to train and test speech-recognition systems

# 语言理解/语义槽值提取



2013年成功应用RNN for SLU

|                       |                    |                |             |               |           |            |             |              |
|-----------------------|--------------------|----------------|-------------|---------------|-----------|------------|-------------|--------------|
| <b>Sentence</b>       | <i>show</i>        | <i>flights</i> | <i>from</i> | <i>Boston</i> | <i>to</i> | <i>New</i> | <i>York</i> | <i>today</i> |
| <b>Slots/Concepts</b> | O                  | O              | O           | B-dept        | O         | B-arr      | I-arr       | B-date       |
| <b>Named Entity</b>   | O                  | O              | O           | B-city        | O         | B-city     | I-city      | O            |
| <b>Intent</b>         | <i>Find Flight</i> |                |             |               |           |            |             |              |
| <b>Domain</b>         |                    |                |             |               |           |            |             |              |



## Investigation of Recurrent-Neural-Network Architectures and Learning Methods for Spoken Language Understanding

Grégoire Mesnil<sup>1,3</sup>, Xiaodong He<sup>2</sup>, Li Deng,<sup>2</sup> and Yoshua Bengio<sup>1</sup>

<sup>1</sup> University of Montréal, Québec, Canada

<sup>2</sup> Microsoft Research, Redmond, WA, USA

COMPARISON BETWEEN MANUALLY LABELED WORD AND ASR OUTPUT

| F1-score | Elman | Jordan | Hybrid | CRF   |
|----------|-------|--------|--------|-------|
| Word     | 94.98 | 94.29  | 95.06  | 92.94 |
| ASR      | 85.05 | 85.02  | 84.76  | 81.15 |

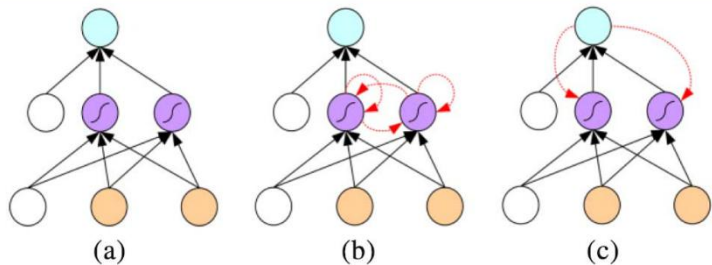


Fig. 1. Three types neural networks. (a) Feed-forward NN; (b) Elman-RNN; (c) Jordan-RNN.

[Mesnil, He, Deng, Bengio, InterSpeech2013]

# 语言理解/语义意图分类

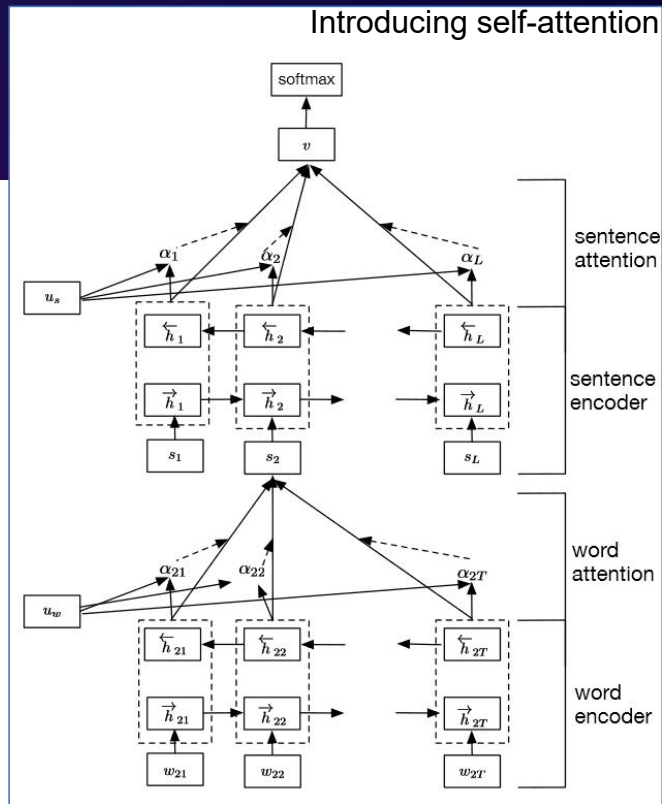


## Hierarchical Attention Net (HAN)

我们于2016年提出的层次化注意力模型 (HAN)能在词、句子、段落、等多个层面来建模理解语言, 判断意图, 并通过对神经元激活的可视化来给出一定程度的可解释性。

GT: 4 Prediction: 4

烤猪, 最好吃了  
带子?  
我不喜欢带子。  
这里的鸡尾酒令人惊叹,  
有趣, 味道好  
下次我再来这个城市时,  
我一定会再来一次  
超推荐



# 语言理解/语义的表征



从自然语言中抽取出语义并将其投影到语义空间以帮助搜索、推荐、分类、问答等应用

抽象的语义表征

通过深度神经网络逐步抽取  
语义上的不变性 (invariance)

自然语言的描述



神经网络

输入

“小明快递了一袋苹果给外公”

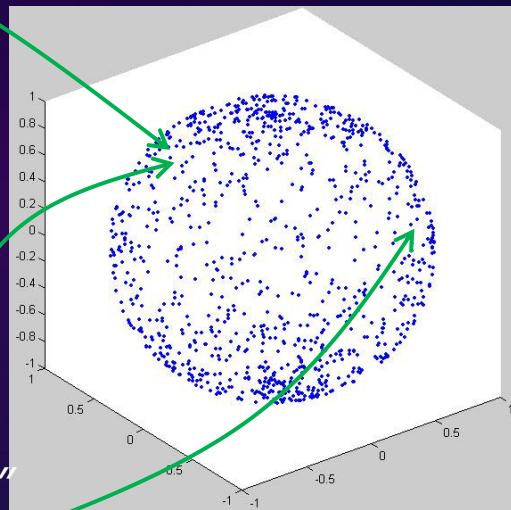
语义相似的描述

“外公从小明那收到了袋红富士”

语义不同的描述

“小明送给女友最新一代的苹果 X”

语义空间



# DSSM: 深度结构化语义模型

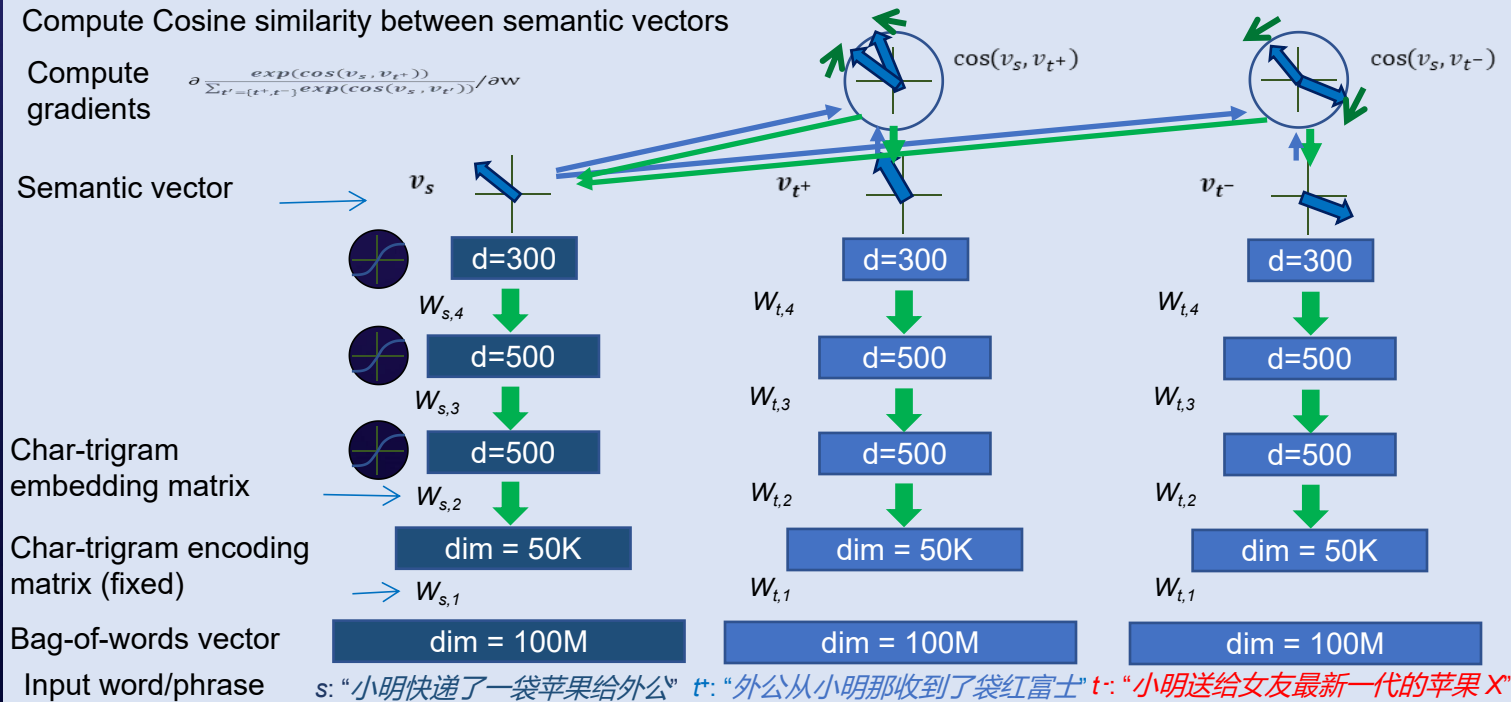


## 基于相对相似度的训练目标函数:

Compute Cosine similarity between semantic vectors

Compute gradients

$$\frac{\partial \exp(\cos(v_s, v_{t^+}))}{\partial w}$$



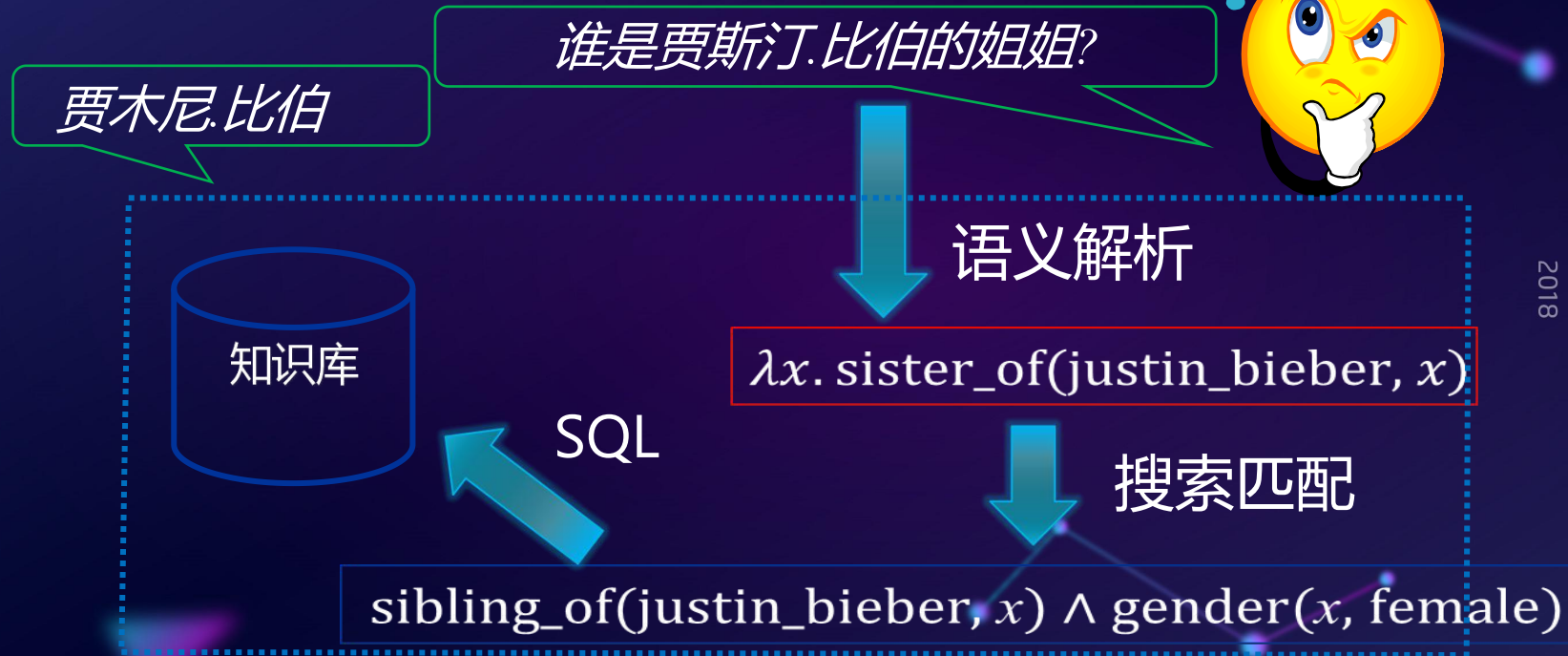
[Huang, He, Gao, Deng, Acero, Heck, “DSSM”, CIKM2013;  
Shen, He, Gao, Deng, Mesnil, “CDSSM”, WWW2014&CIKM2014]



# 知识推理及问答



在连续向量空间表达知识、解析语义、执行推理和应答



2018

# 对话机器人

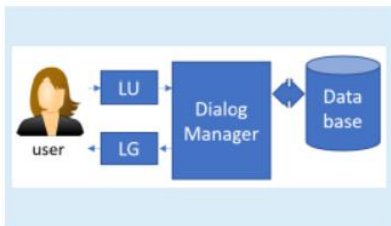


## Early Chatbots



1966

## Task-Completion



1990's

## Personal Assistant



2012

## Social Chatbots



2014



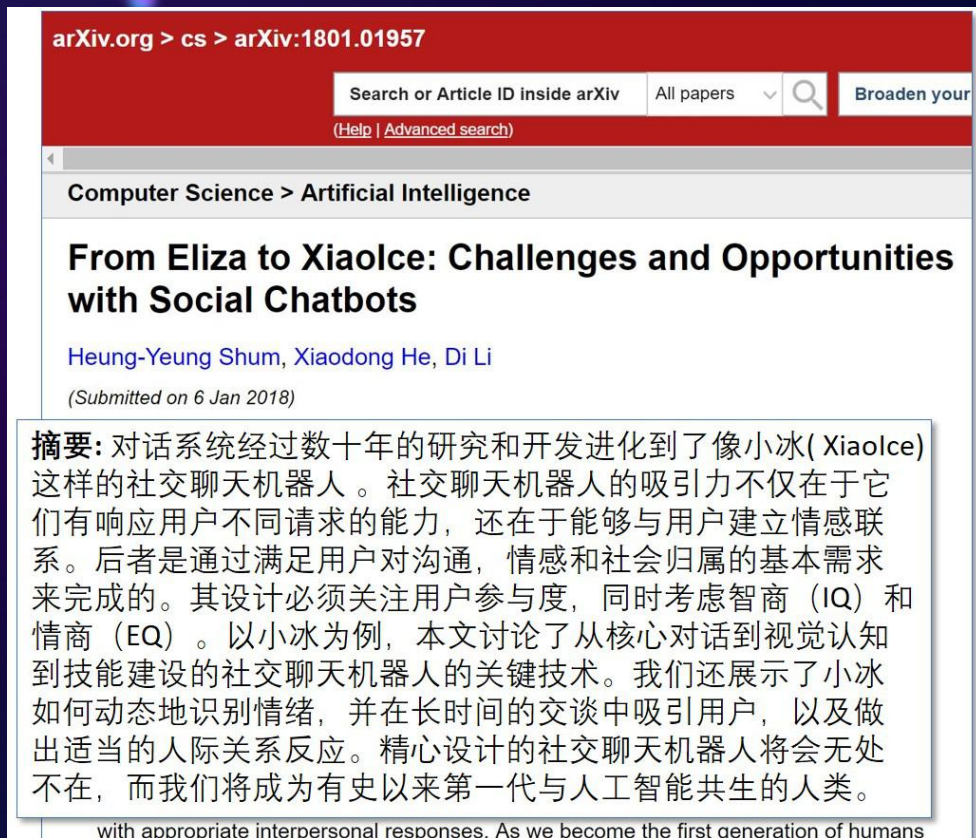
From mimicking humans' behavior,  
to understanding humans' requests,  
to serve humans' proactive and reactive needs,  
and to building emotional connection with humans

# 从语言理解、问答、到人机对话进展显著



“对话机器人不仅需要响应用户的请求，**完成任务**，还需要满足用户对沟通和情感的需求，与用户建立**情感联系**。”“我们将成为有史以来第一代与 AI 共生的人类。”

— “从Eliza到小冰：社交对话机器人的机遇和挑战”，Harry Shum, Xiaodong He, Di Li, in FITEE 2018

A screenshot of an arXiv paper page. The header is red with white text. The main content area is white with a light blue border. The paper title is in bold black font. The authors' names are in blue. The abstract is in black font. The footer is in small black font.

arXiv.org > cs > arXiv:1801.01957

Search or Article ID inside arXiv All papers   Broaden your search

(Help | Advanced search)

Computer Science > Artificial Intelligence

## From Eliza to Xiaolce: Challenges and Opportunities with Social Chatbots

Heung-Yeung Shum, Xiaodong He, Di Li

(Submitted on 6 Jan 2018)

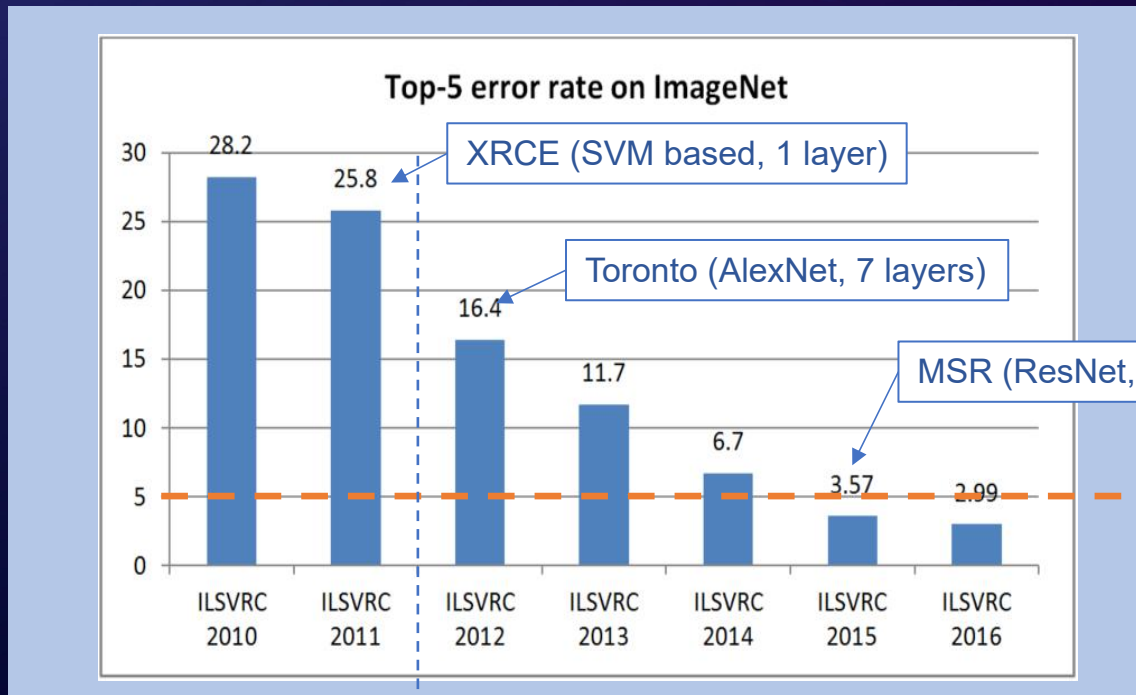
**摘要:** 对话系统经过数十年的研究和开发进化到了像小冰( Xiaolce)这样的社交聊天机器人。社交聊天机器人的吸引力不仅在于它们有响应用户不同请求的能力，还在于能够与用户建立情感联系。后者是通过满足用户对沟通，情感和社会归属的基本需求来完成的。其设计必须关注用户参与度，同时考虑智商 (IQ) 和情商 (EQ)。以小冰为例，本文讨论了从核心对话到视觉认知到技能建设的社交聊天机器人的关键技术。我们还展示了小冰如何动态地识别情绪，并在长时间的交谈中吸引用户，以及做出适当的人际关系反应。精心设计的社交聊天机器人将会无处不在，而我们将成为有史以来第一代与人工智能共生的人类。

with appropriate interpersonal responses. As we become the first generation of humans

# 视觉智能



AI图像识别在ImageNet测试上达到人类水平



人类物体识别错误率约5%

2012 前, 大都是线性模型

2012后, 主流模型是深度神经网络



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Home / Magazine Archive / January 2016 (Vol. 59, No. 1) / Seeing More Clearly / Full Text

NEWS


## Seeing More Clearly

By Neil Savage  
Communications of the ACM, Vol. 59 No. 1, Pages 20-22  
10.1145/2843532  
[Comments](#)

VIEW AS:      SHARE:    



A young boy is holding a baseball bat



Black and white dog jumps over bar

“With careful training, these things (object recognition) actually work very well,” – Rob Fergus

“The complete level, on par with an adult, I think is going to be a long way off,” – Fei-Fei Li

“The overall picture should have the same semantic value as the description,” – Xiaodong He

“If you really understood the image, you could answer a question about it.” – Richard Zemel



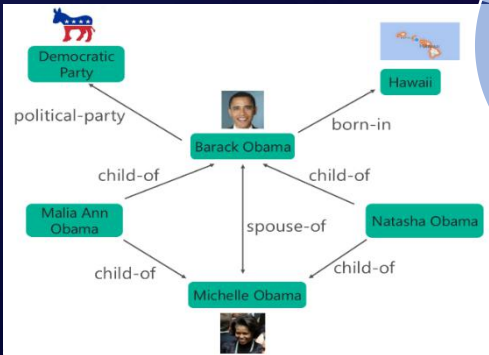
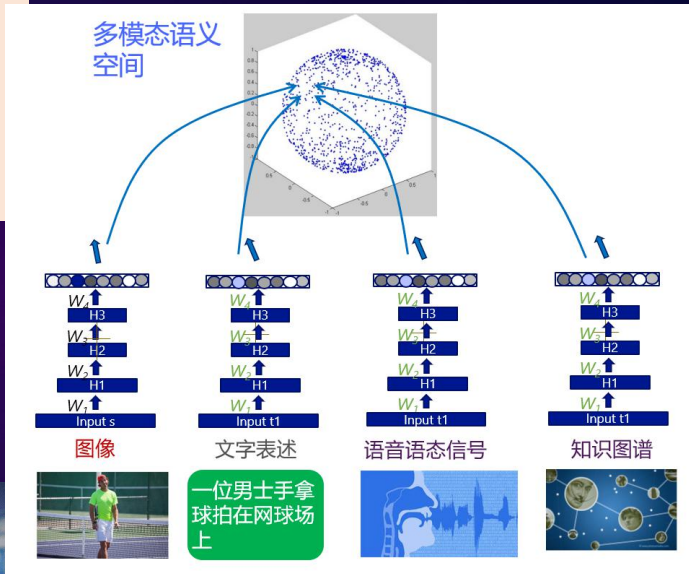
# 多模态智能: 语音,语言,视觉,知识 +



贝拉克·侯赛因·奥巴马，  
美国民主党籍政治家，  
第44任美国总统，为美国历史上第一位非裔美国人（美国黑人）总统。

语音 语言

知识 视觉



# 语言-视觉多模态：三个研究视角



- 表征预训练

- 从原始的语言或图像信号中提取语义表征。往往是将语言和图像信号通过预训练映射到一个连续向量空间。

- 跨模态表征融合与印证

- 在连续向量空间融合多个模态信息。往往是通过跨模态池化模型来融合语言和图像的特征 (multimodal pooling), 及通过注意力模型来为语言和图像的结构建立联接与印证 (grounding)

- 基于多模态任务的模型优化

- 基于特定任务设计优化目标函数及优化算法。比如包括cross-entropy, BLEU; Reinforcement learning, GAN

# 语言-视觉多模态任务

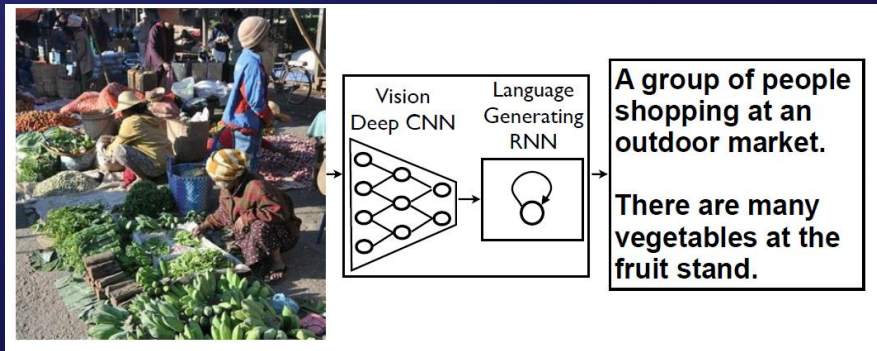


- 图像到文本描述 (image-to-text / image captioning)
  - 理解图像的内容, 生成自然语言来描述图像内容
- 视觉-文本问答 (visual question answering)
  - 基于对图像的理解回答相关的文本问题
- 文本到图像生成 (text-to-image synthesis)
  - 基于对文字描述的理解以生成相应的图像
- 语言-视觉导航, 视觉对话, 跨模态信息检索 ...

# 图像描述 (Image Captioning)



自CVPR 2015 以来的一系列工作



## End-to-End Paradigm:

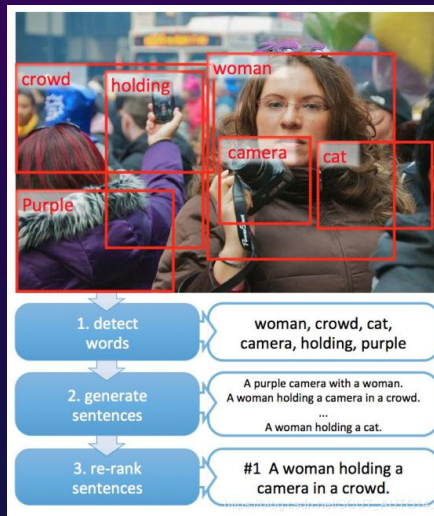
1. Encode image to vector representations (学习图像表征)
2. generate sentences (生成句子)

[Vinyals, Toshev, Bengio, Erhan, "Show and Tell: A Neural Image Caption Generator," CVPR2015]

## Cascade Paradigm:

1. detect words (检测关键物体、概念)
2. generate sentences (生成候选句子)
3. Semantic re-rank sentences (按语义表征排序)

[Fang, Gupta, Iandola, Srivastava, Deng, Dollar, Gao, He, et al., "From Captions to Visual Concepts and Back," CVPR2015]





# Deep Vision

## Deep Vision: Deep Learning in Computer Vision, 2<sup>nd</sup> edition



CVPR 2015 Workshop  
June 11th, 2015, Boston, USA

### Organizing Committee

Y. LeCun, Facebook  
AI&NYU

J. Alvarez, NICTA, Australia

Y. Li, NICTA, Australia

F. Porikli, ANU/NICTA,  
Australia

### Invited Speakers

Yoshua Bengio, U. Montreal

Xiaodong He, MS Research

Stephen Jones, NVIDIA

Randall C. O'Reilly, U. Colorado

Rahul Sukthankar, Google

Andrea Vedaldi, Oxford

Xiaogang Wang, CUHK





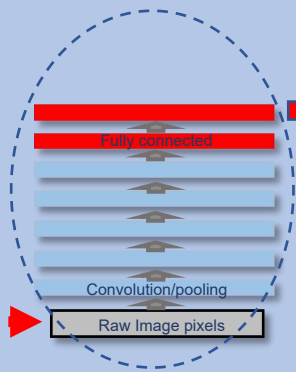
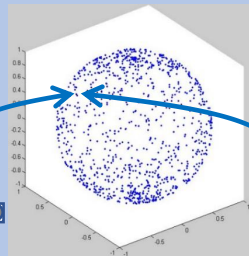
# 建立多模态语义空间：跨模态表征学习



通过深度结构语义模型 (DSSM) 把图像和文字均表征成语义空间内的向量

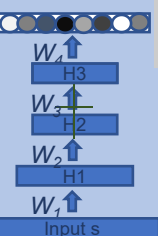
在此空间中进行语义相似度计算，生成最匹配图像内容的文字表述

视觉-语言多模态语义空间

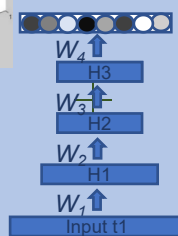


CNN

图像特征



文字表述：一位男士手拿球拍在网球场上



[Fang, Gupta, Iandola, Srivastava, Deng, Dolar, Gao, He, et al., "From Captions to Visual Concepts and Back," CVPR2015]

# 图像描述：理解图像，用语言表达



a baseball player throwing a ball

“一个棒球运动员在扔一个球。”



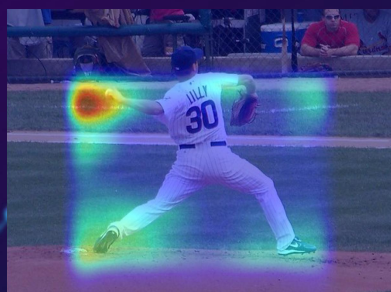
一个**棒球**



一个棒球**运动员**



一个棒球运动员**在扔**



一个棒球运动员在扔一个**球**

# 与实体知识融合



Sasha Obama, Malia Obama, Michelle Obama, Peng Liyuan et al. posing for a picture with Forbidden City in the background.

I think it's Satya Nadella, Harry Shum posing for the camera.



[Guo, Zhang, Hu, He, Gao, "MS-Celeb-1M: A dataset and benchmark for large-scale face recognition", ECCV 2016; Tran, He, Zhang, Sun, et al., "Rich image captioning in the wild," CVPR DeepVision Workshop 2016]

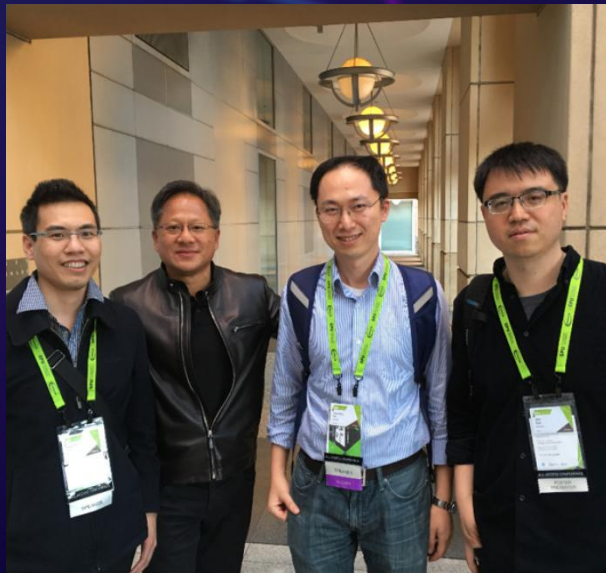


# 图片描述机器人 [http://captionbot.ai]



*"A colorful bird perched on a tree branch."*

一只多彩的小鸟在树枝上鸣叫。



*"Jen-Hsun Huang, Xiaodong He, Jian Sun et al., that are posing for a picture."*

黄仁勋,何晓冬,孙剑等合影留念。



*"A little boy sitting in front of a birthday cake and he seems happy."* — 一位小男孩坐在生日蛋糕前,看起来很高兴。

# 控制语言的语义生成



## Example in CACM 2016

COMMUNICATIONS  
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Home / Magazine Archive / January 2016 (Vol. 59, No. 1) / Seeing More Clearly / Full Text

NEWS  
Seeing More Clearly

By Neil Savage  
Communications of the ACM, Vol. 59 No. 1, Pages 20-22  
10.1145/2843532  
Comments

VIEW AS: [Icons] SHARE: [Icons]

*A young boy is holding a baseball bat*

*Black and white dog jumps over bar*

## Semantic Compositional Networks

**Detected semantic concepts:**  
person (0.998), baby (0.983), holding (0.952), small (0.697), sitting (0.638), toothbrush (0.538), child (0.502), mouth (0.438)

**Semantic composition:**

1. Only using **“baby”**: *a baby in a*
2. Only using **“holding”**: *a person holding a hand*
3. Only using **“toothbrush”**: *a pair of toothbrush*
4. Only using **“mouth”**: *a man with a toothbrush*
5. Using **“baby”** and **“mouth”**: *a baby brushing its teeth*

**Overall caption generated by the SCN:**  
*a baby holding a toothbrush in its mouth*

**Influence the caption by changing the tag:**

6. Replace **“baby”** with **“girl”**: *a little girl holding a toothbrush in her mouth*
7. Replace **“toothbrush”** with **“baseball”**: *a baby holding a baseball bat in his hand*
8. Replace **“toothbrush”** with **“pizza”**: *a baby holding a piece of pizza in his mouth*

2018



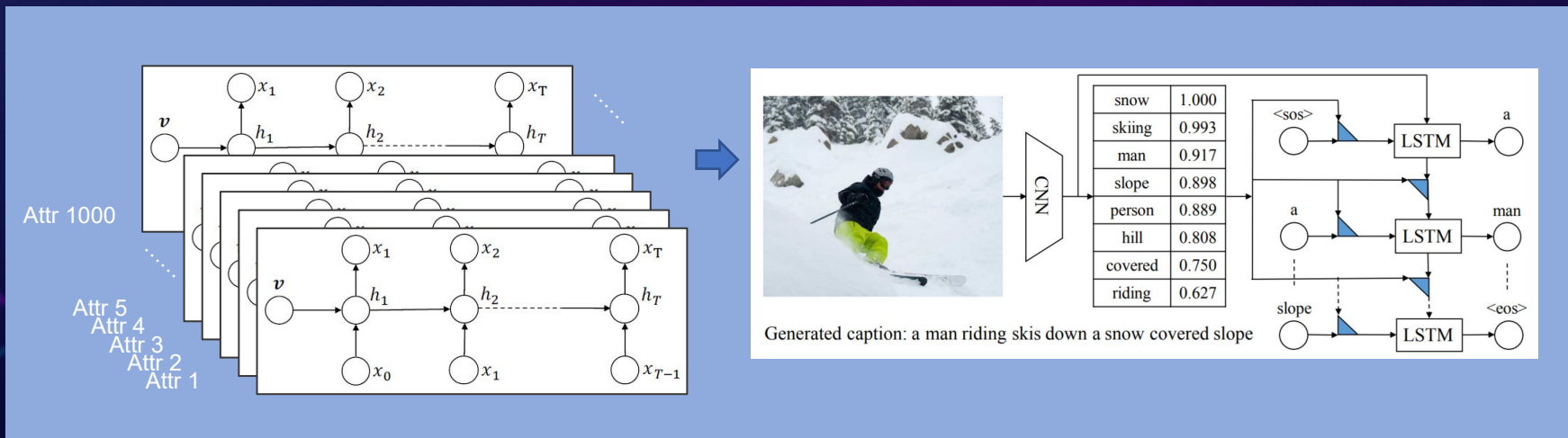
# 语义组合网络



## Semantic Compositional Networks (SCN)

A *very wide* Model (as wide as 1000 LSTM slices)

- Conceptually, learn 1000 LSTMs, one for each semantic attributes.
- Combine these 1000 LSTMs, weighted by attributes' likelihood.
- Run tensor decomposition to reduce #parameters to fit in GPU

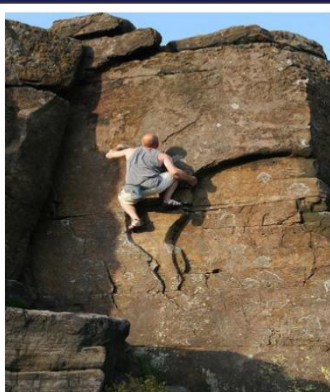


2018

# 表达情感和风格



让AI用语言来表达浪漫或者幽默的风格 - StyleNet



**CaptionBot:** A man on a rocky hillside next to a stone wall.

**Romantic:** A man uses rock climbing to overcome the obstacle in the life.

**Humorous:** A man is climbing the rock like a lizard.

**CaptionBot:** A dog runs in the grass.

**Romantic:** A dog runs through the grass to meet his lover.

**Humorous:** A dog runs through the grass in search of the missing bones.

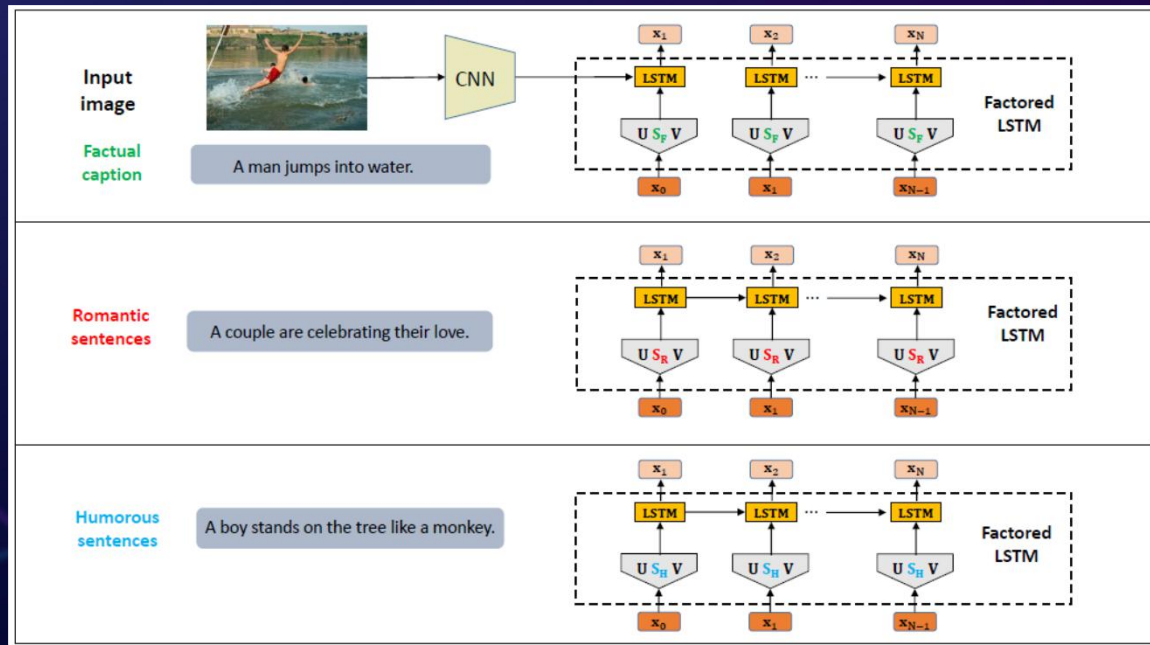


[Gan, Gan, He, Gao, Deng, "StyleNet", CVPR2017]

# 表达情感和风格



让AI用语言来表达浪漫或者幽默的风格 - StyleNet



2018

[Gan, Gan, He, Gao, Deng, "StyleNet", CVPR2017]

# 生成带情感的语言



## 让AI在语言表达中加入情感



分类: 户外, 女士

语义: 一位穿着蓝色T恤的女士

情感+: 美丽得像一位天使!



分类: 女士, 小狗

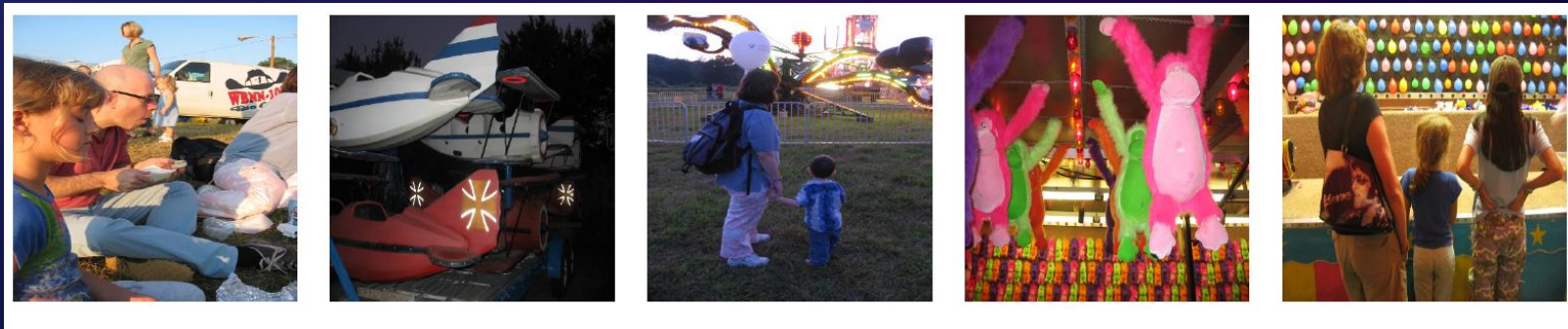
语义: 一位女士和一只狗在相机前摆姿势

情感+: 啊真可爱, 我是说这只小狗耶 😊

# 看图生成故事 (Storytelling)



看一组照片写日记



孩子们今天去参加了一个嘉年华会。那有很多不一样的酷酷的东西。有些孩子在玩空中活动。这里还有巨大的恐龙。一天结束了，孩子们玩得很开心。



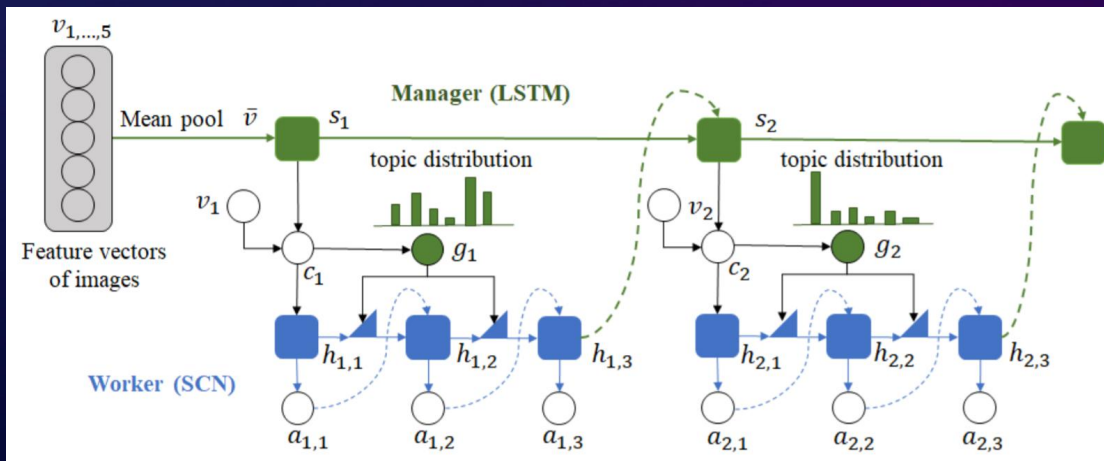
# 看图生成故事: 生成多句相关句子



双层生成模型:

上层 (Manager) : 生成一系列主题 (topics)

下层 (Worker) : 按主题展开成句子



[Huang, Gan, et al., "Hierarchically structured reinforcement learning for topically coherent visual story generation," AAAI2019]

# 视觉-语言多模态机器问答 (Visual QA)



- Answer natural language questions according to the content of a reference image.



**Question:**  
What are sitting  
in the basket on  
a bicycle?

Image  
Question  
Answering  
(IQA)

**Answer:**

→ dogs

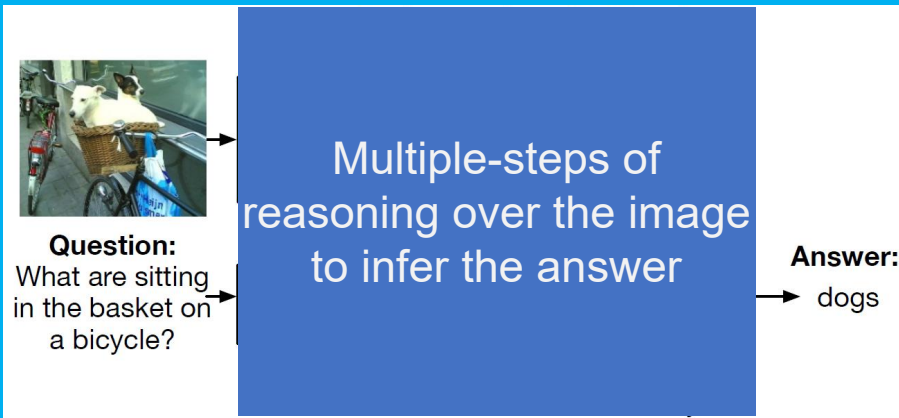
# 从图片描述到图文问答：推理能力



To answer a question about a image:

Need to understand subtle relationships among multiple objects

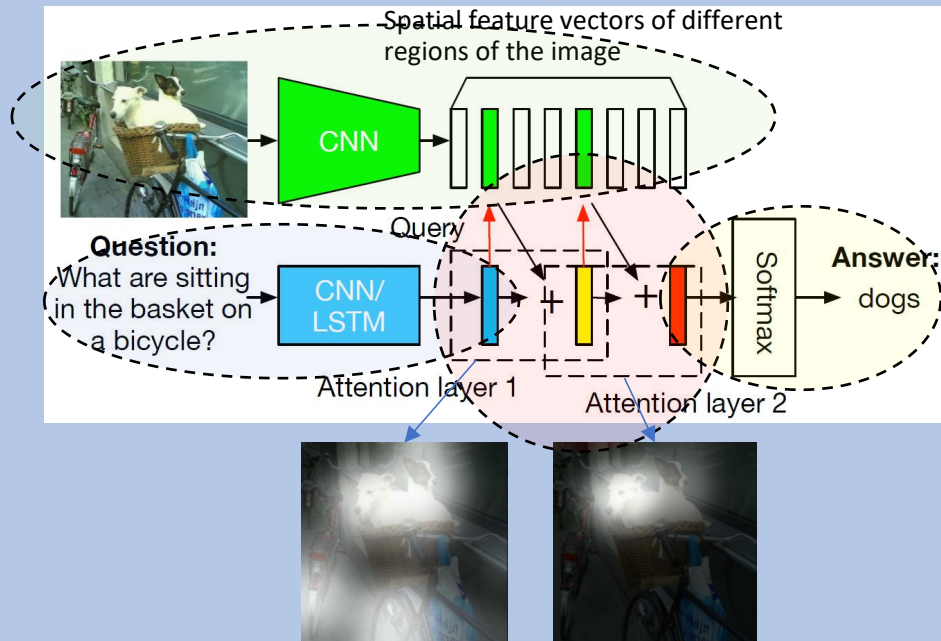
Need to focus on the specific regions that are relevant to the answer.



# 堆叠注意力网络 (Stacked Attention Net)

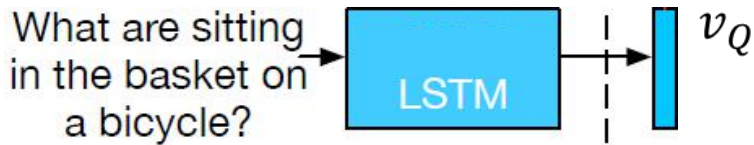
SANs perform multi-step reasoning

1. Question model
2. Image model
3. Multi-level attention model
4. Answer predictor
5. End-to-end learning using SGD

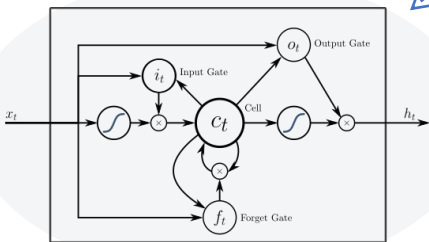


[Yang, He, Gao, Deng, Smola, "Stacked Attention Networks," CVPR 2016]

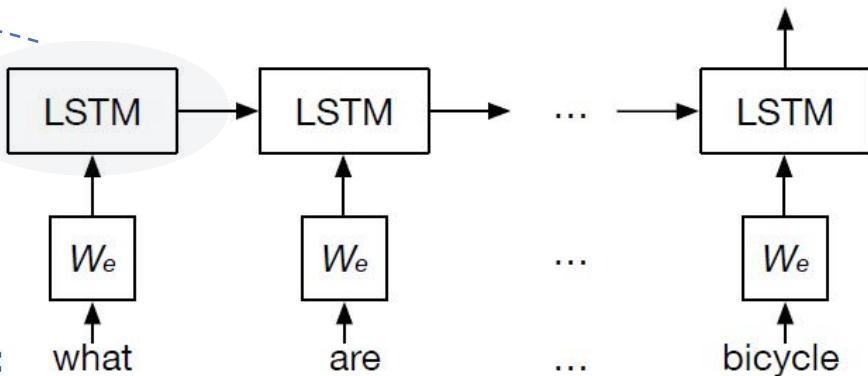
# 提取语言表征



A LSTM cell



Question:





# 提取视觉表征

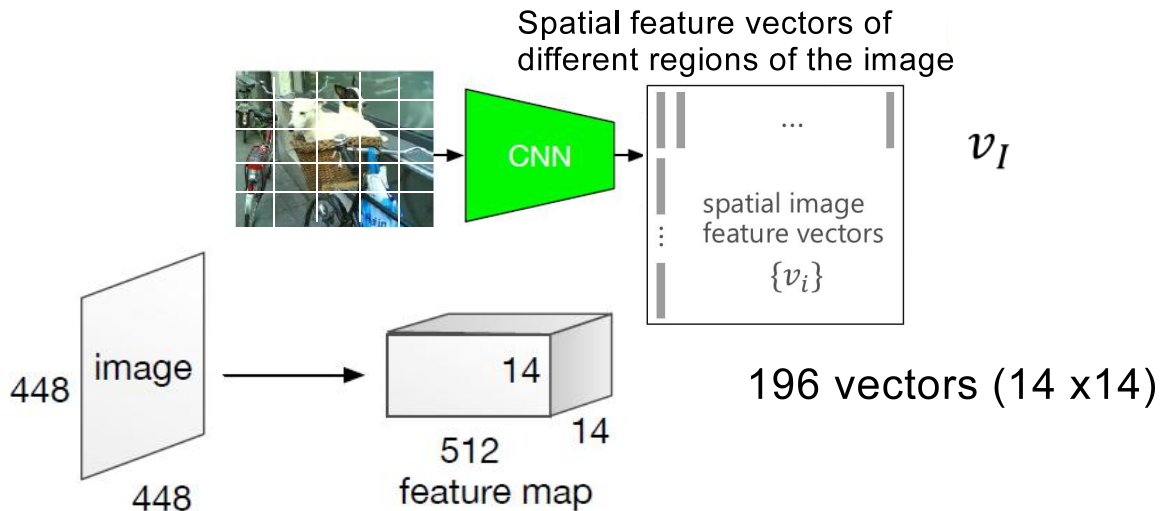
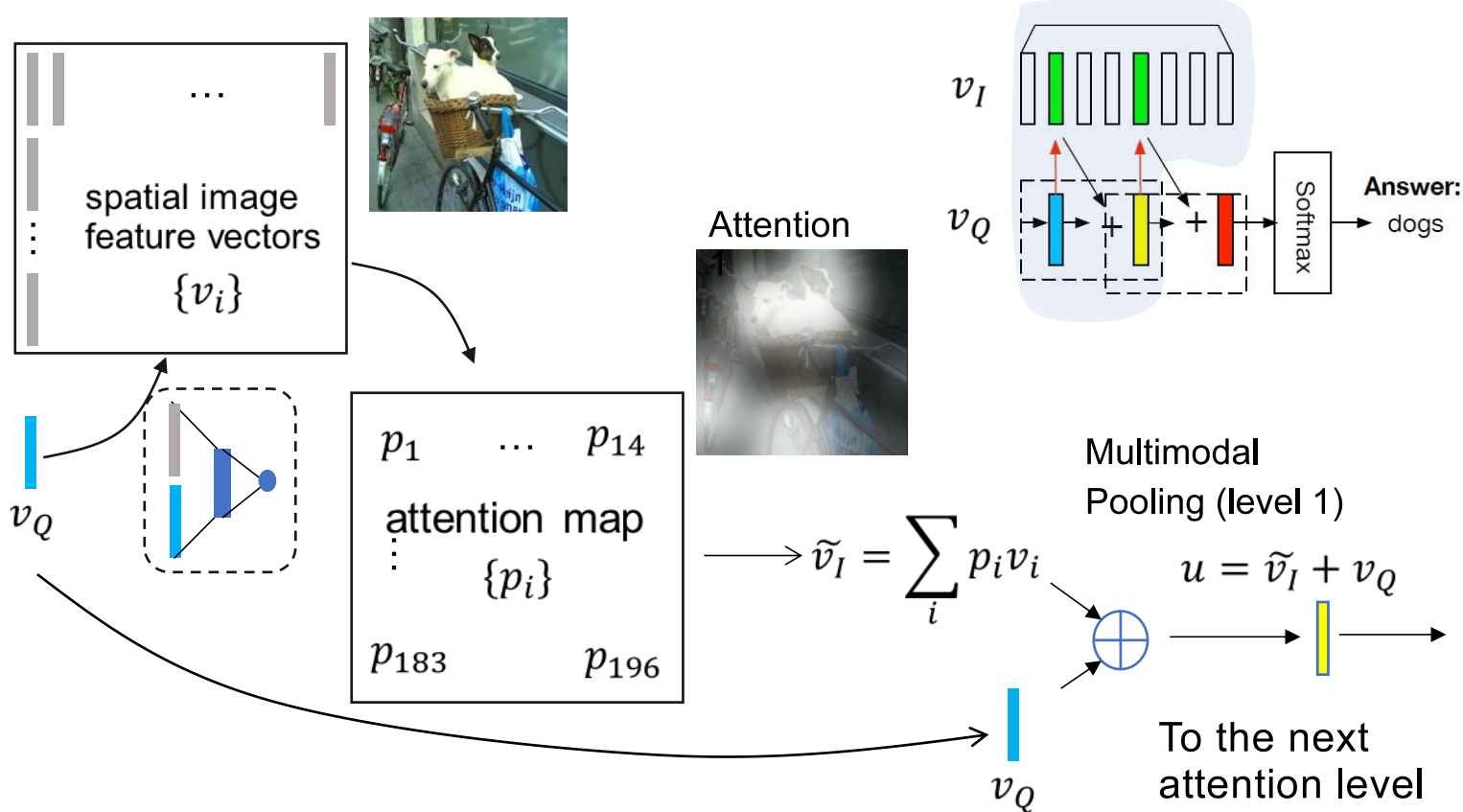


Figure 2: CNN based image model

$$f_I = \text{CNN}_{vgg}(I). \quad v_I = \tanh(W_I f_I + b_I)$$

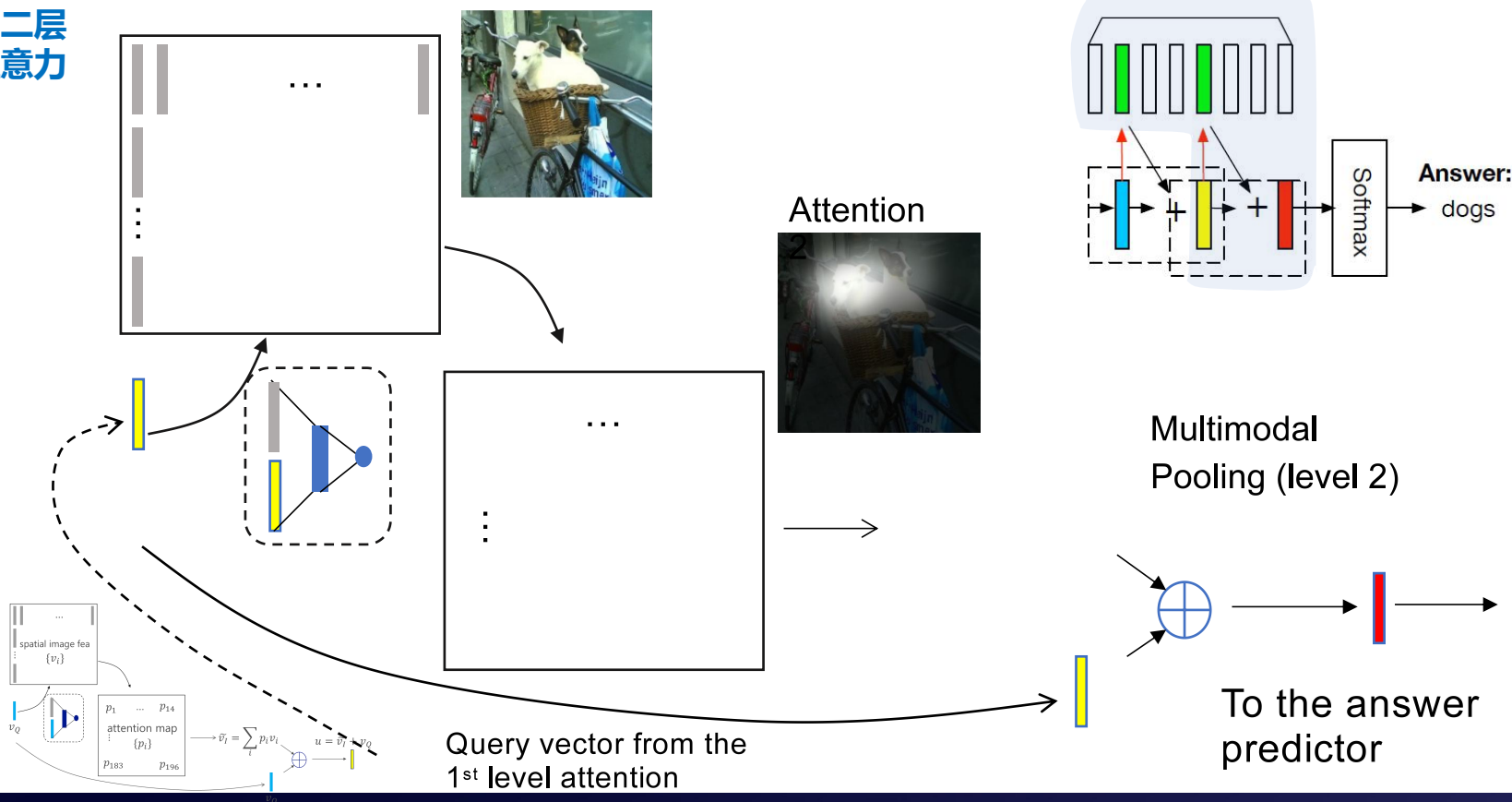
# 跨模态表征融合与印证(Pooling & Grounding)

第一层  
注意力



# 跨模态表征融合与印证(Pooling & Grounding)

第二层  
注意力



# Bottom-Up and Top-Down Attention (BUTD)

## 注意力模型的一个新视角

In human visual system, there are two kinds of attentions:

*Top-down attention:*

proactively initiated by the current task (e.g., look for something)

*Bottom-up attention:*

spontaneously emerge from visual salient stimuli

### **Bottom-Up and Top-Down Attention for Image Captioning and Visual Question Answering**

Peter Anderson<sup>1\*</sup> Xiaodong He<sup>2</sup> Chris Buehler<sup>3</sup> Damien Teney<sup>4</sup>  
Mark Johnson<sup>5</sup> Stephen Gould<sup>1</sup> Lei Zhang<sup>3</sup>

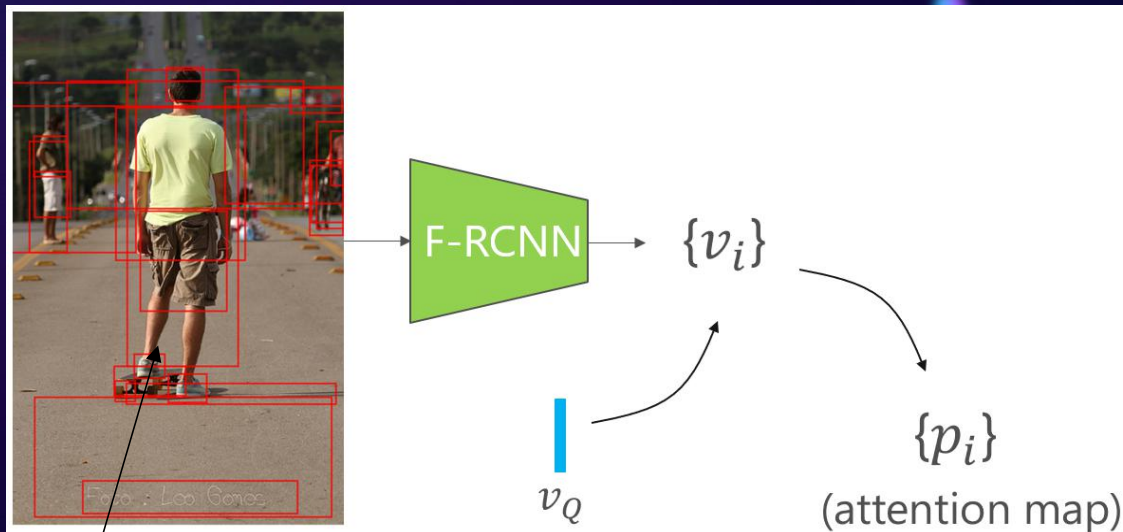
<sup>1</sup>Australian National University <sup>2</sup>JD AI Research <sup>3</sup>Microsoft Research <sup>4</sup>University of Adelaide <sup>5</sup>Macquarie University  
<sup>1</sup>firstname.lastname@anu.edu.au, <sup>2</sup>xiaodong.he@jd.com, <sup>3</sup>{chris.buehler, leizhang}@microsoft.com  
<sup>4</sup>damien.teney@adelaide.edu.au, <sup>5</sup>mark.johnson@mq.edu.au



# Bottom-Up and Top-Down Attention (BUTD)

Bottom-Up attention:

- Use F-RCNN to detect key objects
- Compute spatial feature vector for each object
- Keep complete visual information for each object



**Attend on actual objects**, rather than on uniform grid regions like conventional top-down attention

# Bottom-Up and Top-Down Attention (BUTD)

Adopt similar terminology to humans' attention system:

- attention mechanisms driven by non visual or task-specific context as 'top-down'
- purely visual feed-forward attention mechanisms as 'bottom-up'.

Overall Attention Net for VQA:

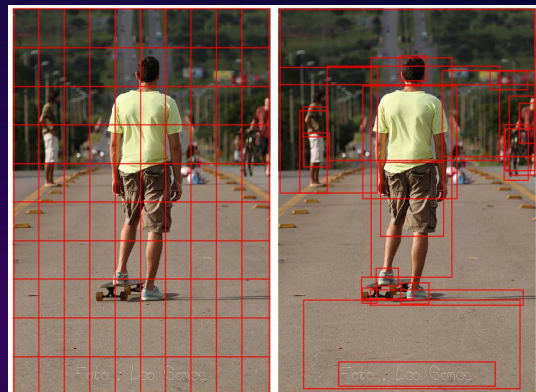
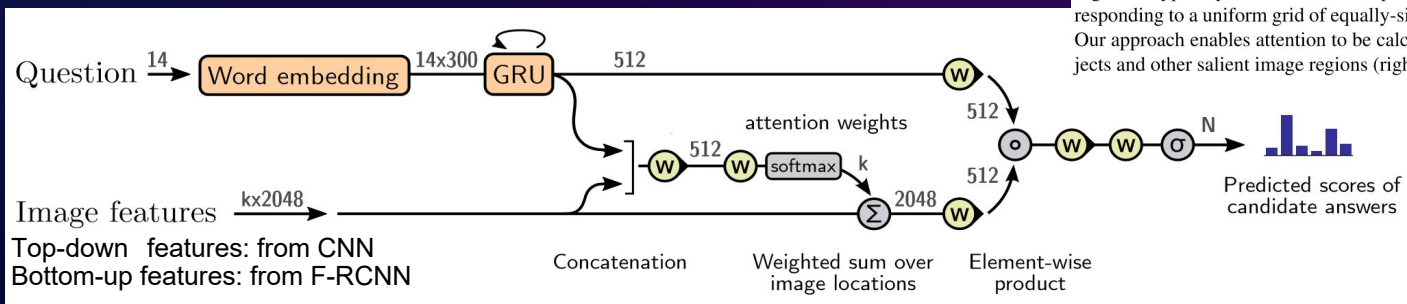


Figure 1. Typically, attention models operate on CNN features corresponding to a uniform grid of equally-sized image regions (left). Our approach enables attention to be calculated at the level of objects and other salient image regions (right).

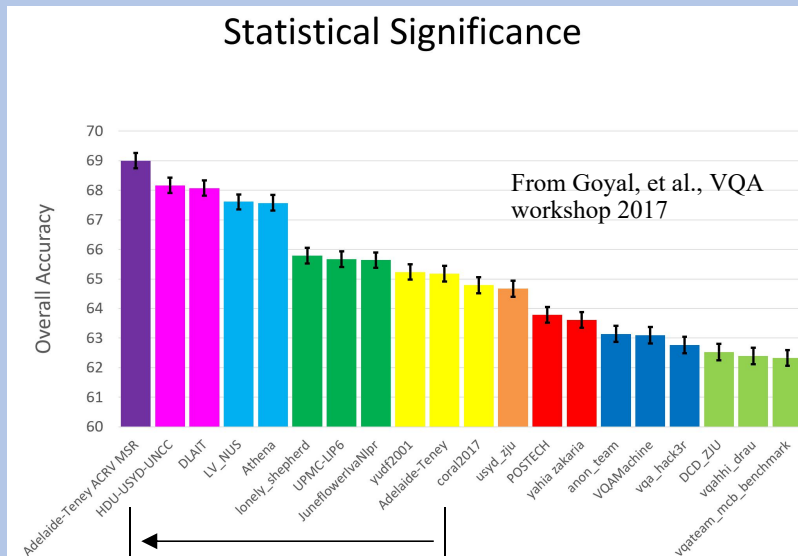
# Attention Example



Question: What room are they in? Answer: kitchen

Figure 6. VQA example illustrating attention output. Given the question ‘What room are they in?’, the model focuses on the stove-top, generating the answer ‘kitchen’.

# VQA Challenge @ CVPR2017



← Because of **Bottom-up Attention**

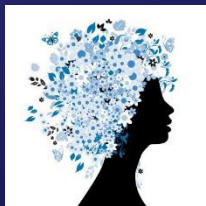


- [1] Bottom-Up and Top-Down Attention for Image Captioning and Visual Question Answering, CVPR18
- [2] Tips and Tricks for Visual Question Answering: Learnings from the 2017 Challenge, CVPR18

此后几乎所有的VQA队伍都使用了“Bottom-Up and Top-Down (BUTD)”注意力模型或其变种。



# VQA应答机器人



那两把蓝色椅子之间是什么？



2018

一把伞

【Yang, He, Gao, Deng, Smola, CVPR2016】



# 视觉-语言多模态导航



结合语言理解和对环境的视觉信息建模，智能代理能按指令从一个地方走到另一个地方

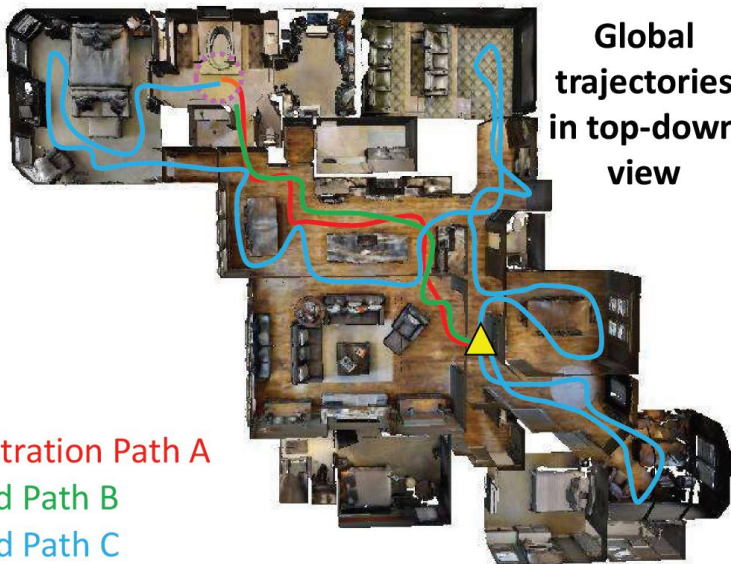
## Instruction

Turn right and head towards the *kitchen*. Then turn left, pass a *table* and enter the *hallway*. Walk down the hallway and turn into the *entry way* to your right *without doors*. Stop in front of the *toilet*.

## Local visual scene



## Global trajectories in top-down view



 Initial Position

 Target Position

 Demonstration Path A

 Executed Path B

 Executed Path C

[Anderson et al., CVPR2018;  
Wang et al., CVPR 2019]

# 理解语言, 用绘画来表达 (Text-to-Image)

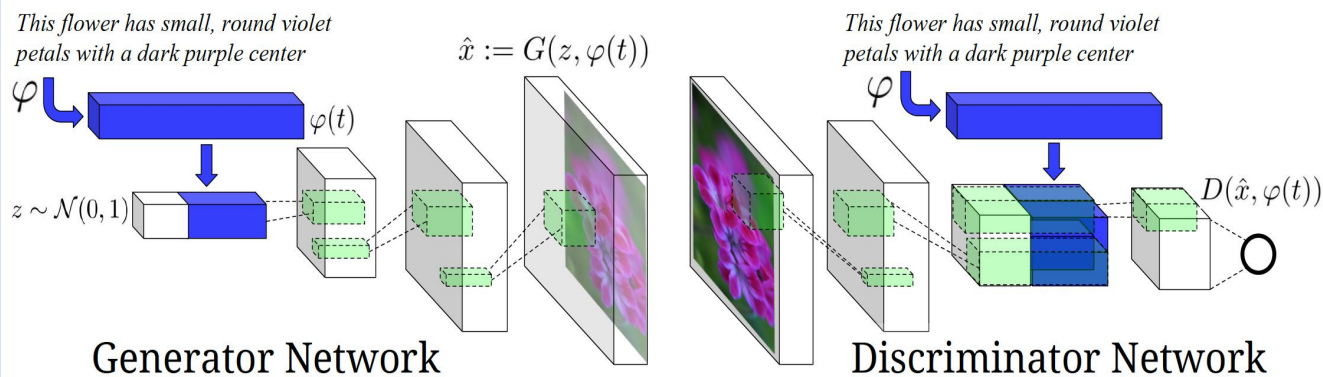


Figure 2. Our text-conditional convolutional GAN architecture. Text encoding  $\varphi(t)$  is used by both generator and discriminator. It is projected to a lower-dimensions and depth concatenated with image feature maps for further stages of convolutional processing.

this small bird has a pink breast and crown, and black primaries and secondaries.

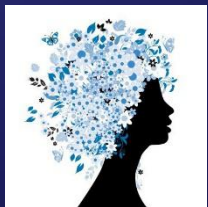


Objective function:

$$\min_G \max_D V(D, G) = \mathbb{E}_{\mathbf{x} \sim p_{\text{data}}(\mathbf{x})} [\log D(\mathbf{x})] + \mathbb{E}_{\mathbf{z} \sim p_{\mathbf{z}}(\mathbf{z})} [\log(1 - D(G(\mathbf{z})))]$$

[Reed et al., "Generative adversarial text-to-image synthesis", ICML2016]

# 绘画机器人(AttnGAN): 精准理解,精确绘制



一只红羽毛白肚子的短咀小鸟

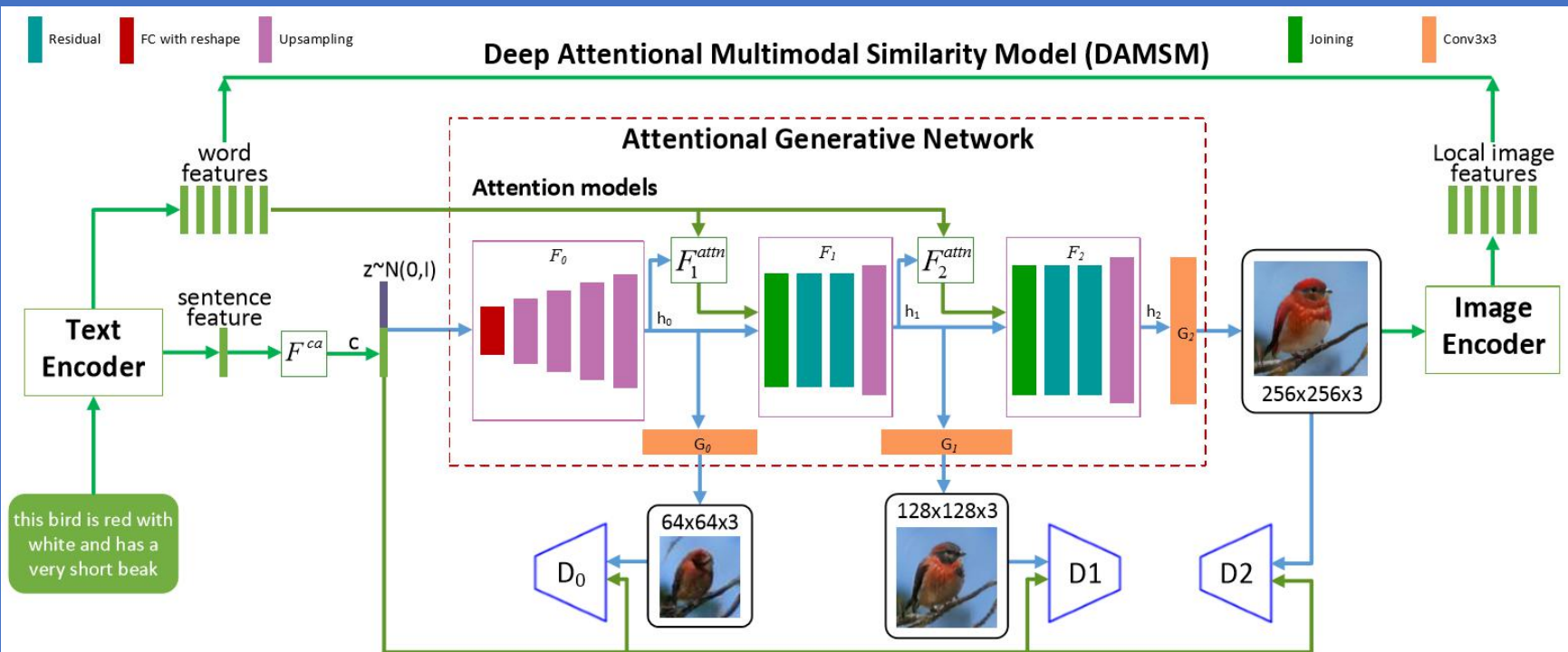


2018

【Xu, Zhang, Huang, Zhang, Gan, Huang, He, "AttnGAN," CVPR2018】



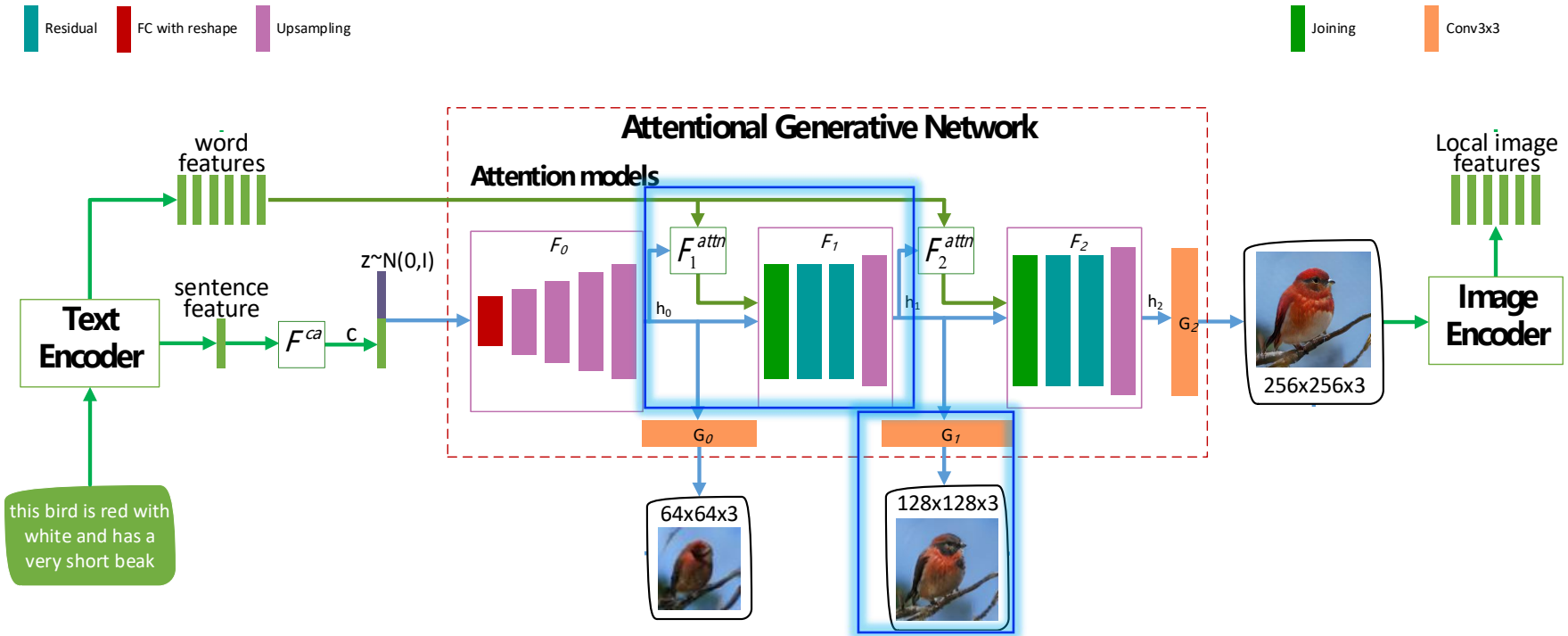
# AttnGAN: GAN with Attention



The final objective function:  $L = L_{GAN} + \lambda L_{DAMSM}$

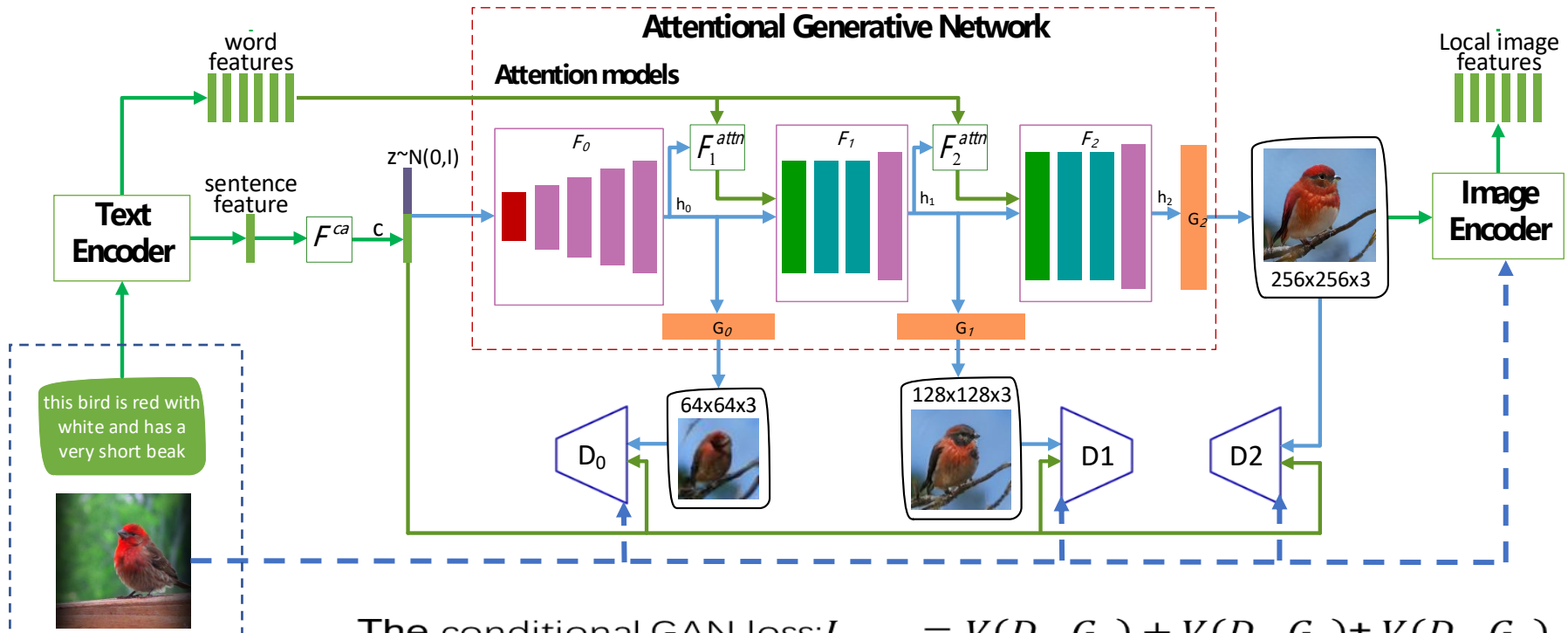


# AttnGAN: Attentive Generative Adversarial Networks



- In following stages, attention models are built.
  - For each region feature of previous generated image, compute its word-context vector.
  - Concatenate previous image region features (e.g.,  $h_0$ ) and word-context vectors to generate the new image.

# AttnGAN: Attentive Generative Adversarial Networks

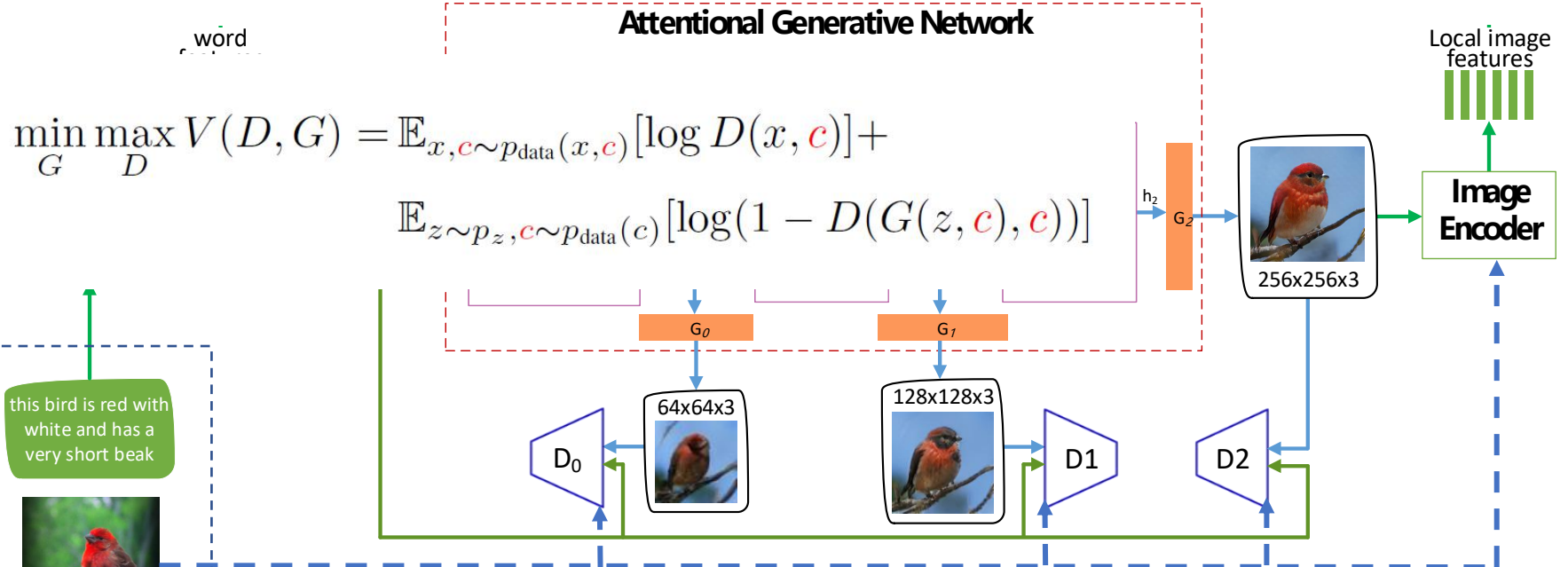


The conditional GAN loss:  $L_{GAN} = V(D_0, G_0) + V(D_1, G_1) + V(D_2, G_2)$

Training pairs

this bird is red with white and has a very short beak

# AttnGAN: Attentive Generative Adversarial Networks



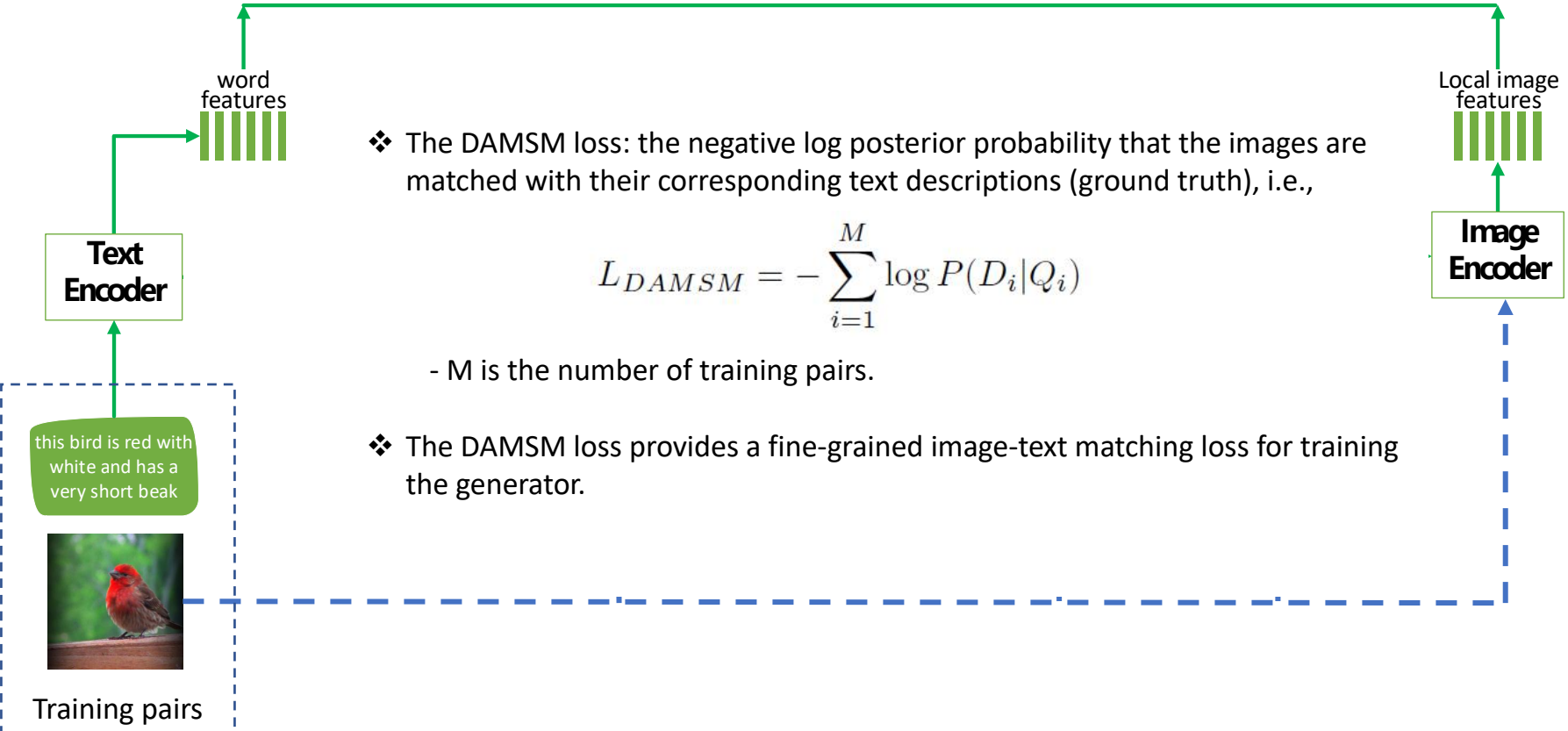
this bird is red with white and has a very short beak

Training pairs

The conditional GAN loss:  $L_{GAN} = V(D_0, G_0) + V(D_1, G_1) + V(D_2, G_2)$

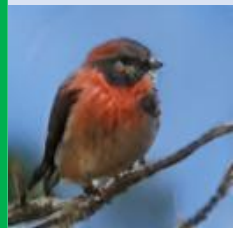
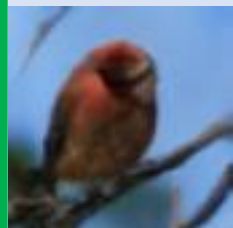
# AttnGAN: Attentive Generative Adversarial Networks

## Deep Attentional Multimodal Similarity Model (DAMSM)



# 语言-视觉印证: Grounding via Attention

this bird is red with white and has a very short beak.





# AI的想象: Artificial Imagination



this bird has wings that are blue and has a red belly



this bird has a green crown black primaries and a white belly



this bird has a yellow crown and a black eye ring that is round



a small red and white bird with a small curved beak



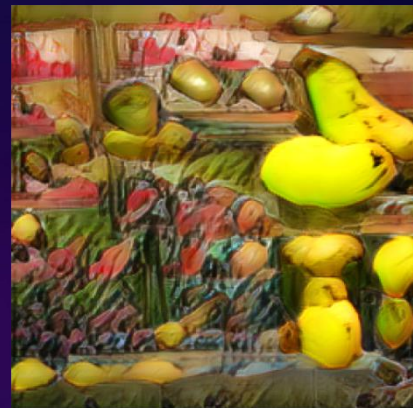
# 更多绘画



a herd of sheep grazing on a lush green field



a fruit stand display with bananas and kiwi



an old clock next to a light post in front of a steeple



a wild pack of family dogs came running through the yard one day



# AI+Art

## JDAI与中央美术学院合作

新华社客户端  
新主流·新体验

立即体验

北京：研究人员尝试把人工智能“浸入”绘画艺术

中国聚焦  
2019-03-03 17:00:32

来源：新华社

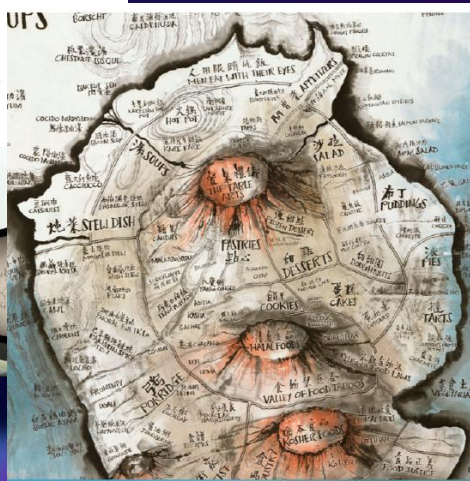
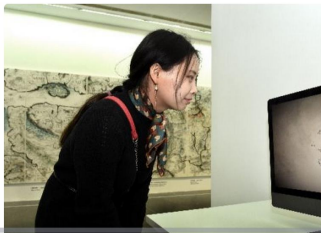
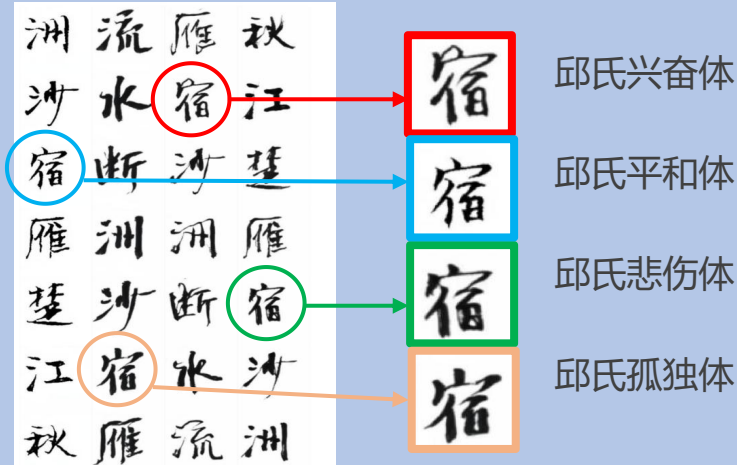


Figure 1: An example of Mind Map

永和九年  
永和九年





# 领域进展



[Reed et al., Generative adversarial text-to-image synthesis, ICML, **2016**]



[Xu et al., AttnGAN: Fine-grained text to image generation with Attentional GANs, CVPR **2018**]



[Brock et al., BigGAN: A New State of the Art in Image Synthesis, ICLR **2019**]

# 多模态智能的下一步



- 融合多个子领域（语言、视觉、语音、知识工程...）
- 跨模态预训练、概念/实体grounding、神经-符号处理机
- 通过复杂跨模态问题驱动基础研究
- 打造更成熟和多元化的实际多模态智能应用



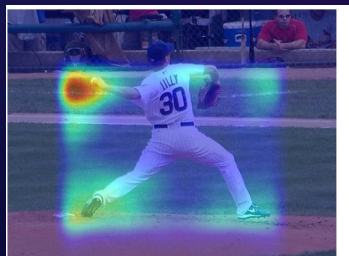
# 跨越语言 and 视觉的理解和表达



Universal Chatbot, Digital Assistant, Mixed Reality, Robot w/ Cognition ...

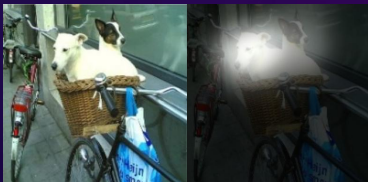
Multimodal Intelligence: perception, reasoning, pooling, grounding and creation across language & vision

## Image-to-language



ball (1.00)  
a baseball player throwing a **ball**

## Visual QA/Dialog



Q: what are sitting in the basket on a bicycle?  
A: dogs.

## Language-to-image

This bird is red with white and has a very short beak



Deep **Representation** Learning / Deep **Attention** Mechanisms

THANKS

[xiaodong.he@jd.com](mailto:xiaodong.he@jd.com)

智汇京东 · 开放共赢



2018