# Show and Tell: A Neural Image Caption Generator

Vinyals et al. (Google)

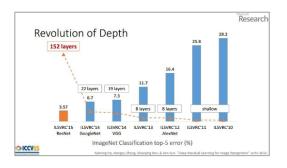
The IEEE Conference on Computer Vision and Pattern Recognition, 2015

## The Problem

- ► Image Caption Generation
- Automatically describe content of an image
- ightharpoonup Image ightarrow Natural Language
- Computer Vision + NLP
- ► Much more difficult than image classification/recognition

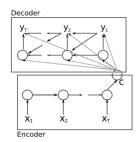
## Background

- Success in image classification/recognition
- Close to human level performance
- Deep CNN's, Big Datasets
- Image to fixed length vector



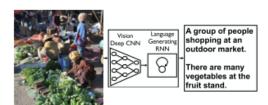
## Background

- Machine Translation
- ► Language generating RNN's
- Decoder-Encoder framework
- Maximize likelihood of target sentence



### Idea

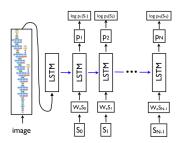
- Combine Vision CNN with Language RNN
- Deep CNN as encoder
- Language Generating RNN as decoder
- ▶ End to end model  $I \rightarrow S$
- ► Maximize p(S|I)



### The Model

## Neural Image Caption (NIC)

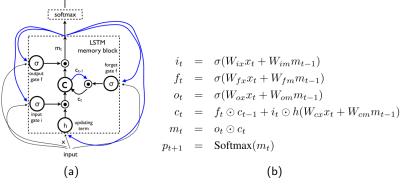
- ► CNN: 22 layer GoogleNet
- LSTM for modeling  $\log p(S|I) = \sum_{t=0}^{N} \log p(S_t|I, S_0, \dots, S_{t-1})$
- ▶ Word embedding W<sub>e</sub>



## Language LSTM

word prediction

- Predicts next word in sentence
- Memory cell for longer memory
- $ightharpoonup S_t$  one-hot vectors + START/END token
- ►  $x_{-1} = \text{CNN}(I)$ ,  $x_t = W_e S_t$ ,  $p_{t+1} = \text{LSTM}(x_t)$



## **Training**

- ▶ Loss function  $L(I, S) = -\sum_{t=1}^{N} \log p_t(S_t)$
- CNN pre-trained on ImageNet
- $\blacktriangleright$  Minimize w.r.t. LSTM parameters,  $W_e$  and CNN top layer
- SGD on mini-batches
- Dropout and ensembling
- 512 dimensional embedding

## Generation

- Give  $x_{-1} = CNN(I)$
- $ightharpoonup x_0 = W_e S_0$ ,  $S_0$  START token
- ► Sample word S<sub>1</sub>
- ► Feed W<sub>e</sub>S<sub>1</sub> to LSTM
- ▶ BeamSearch, beam size 20

- MSCOCO dataset: 80k train, 40k eval and test
- ▶ 5 human made captions per image
- M1-M5 human judgements

∀	M1 🔻	M2 —	М3 —	M4 =	M5 ₩
Human <sup>[5]</sup>	0.638	0.675	4.836	3.428	0.352
Google <sup>[4]</sup>	0.273	0.317	4.107	2.742	0.233
MSR <sup>[11]</sup>	0.268	0.322	4.137	2.662	0.234

Metric	BLEU-4	METEOR	CIDER
NIC	27.7	23.7	85.5
Random	4.6	9.0	5.1
Nearest Neighbor	9.9	15.7	36.5
Human	21.7	25.2	85.4

Table 1. Scores on the MSCOCO development set.

A person riding a motorcycle on a dirt road.



A group of young people playing a game of frisbee.







Two dogs play in the grass.



Two hockey players are fighting over the puck.

A close up of a cat laying on a couch.



Describes with minor errors

A skateboarder does a trick





side of the road.



Somewhat related to the image

A dog is jumping to catch a



A refrigerator filled with lots of food and drinks.



A yellow school bus parked in a parking lot.



- Improved Flickr8k, Flickr30k, PASCAL BLEU scores
- Need better evaluation metrics
- ▶ 80% of top-1 in training set
- ▶ 50% of top-15 in training set
- Similiar diversity as human captions

A man throwing a frisbee in a park.

A man holding a frisbee in his hand.

A man standing in the grass with a frisbee.

A close up of a sandwich on a plate.

A close up of a plate of food with french fries.

A white plate topped with a cut in half sandwich.

A display case filled with lots of donuts.

A display case filled with lots of cakes.

A bakery display case filled with lots of donuts.



Trained word embeddings W<sub>e</sub>

Word	Neighbors
car	van, cab, suv, vehicule, jeep
boy	toddler, gentleman, daughter, son
street	road, streets, highway, freeway
horse	pony, donkey, pig, goat, mule
computer	computers, pc, crt, chip, compute

- ► Captures semantics from the language data
- ▶ Independent of vocubulary size

## Summary

- End-to-end model (Encoder-Decoder)
- Vision CNN + Language generating RNN
- Maximize likelihood of S given I
- State of the art results on major datasets
- Datasets are limiting: Unsupervised approaches?