

SentiCap: Generating Image Descriptions with Sentiments

Alexander Mathews^{*1}, Lexing Xie^{*1 *2}, Xuming He^{*2 *1}



This is a dog resting on a computer.

A white shaggy beautiful dog laying its head on top of a computer keyboard.



A motorcycle parked behind a truck on a green field.

A beat up, rusty motorcycle on unmowed grass by a truck and trailer.

Image Captions and Sentiment

Sentiment is common in everyday language

Sentiment drives decision making

Where to eat for lunch

What to read

Who to vote for



I had a very tasty burger with some crunchy fries.

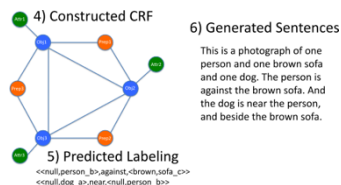
My overcooked burger and soggy fries.

With sentiment we can:

- Make more interesting and more human captions
- change the way people feel about an image

Contents

Related work



Dataset construction

Use the most appropriate of the word pairs below to describe the scene in a positive or negative way.

Describe all the important parts of the scene.

- Do not start the sentences with "There is".
- Do not describe irrelevant details.
- Do not describe what a person might say.
- Do not give single proper nouns.
- The sentence should contain at least 5 words.

Example Descriptions:

- a man swinging a bat during a baseball game
- a baseball player bending over to hit a ball
- a baseball player hitting a baseball at home base

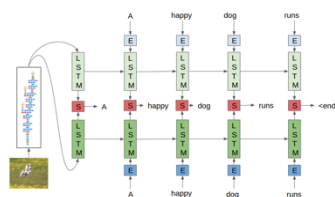
Word Pairs

swing	bat	good	man
good	game	beautiful	home
good	game	good	field
bat	home	good	man
good	man	good	ball

Description

None of the word pairs are appropriate

Switching RNN Model



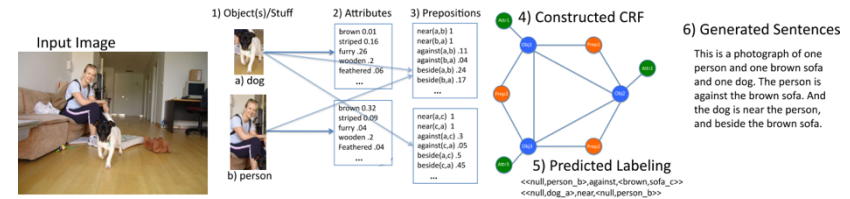
Evaluation + Results



Related work: Image to Sentence

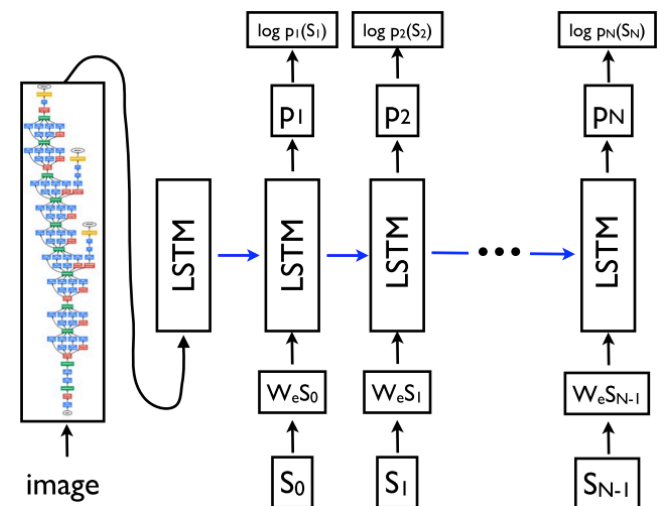
Nearest neighbour images + caption transfer (Farhadi, 2010)

Detectors for nouns, scenes, actions. With template filling and/or language model (Kulkarni, 2011)



Convolution Neural Network + Recurrent neural network

(Vinyals, 2014), (Donahue, 2015), (Karpathy, 2015), (Mao, 2014), (Kiros, 2014)



Related Work: Sentiment

Recognising sentiment has been studied extensively

Used in areas such as:

Predicting movie reviews (Pang, 2005)

Understanding public opinion (Tumasjan, 2010)

Exploring large text collections (Mei, 2007)

Predicting sentiment of images (Borth 2013)

Using Adjective Noun Pair (ANP) detectors

Generating image captions with sentiment is still an open problem.

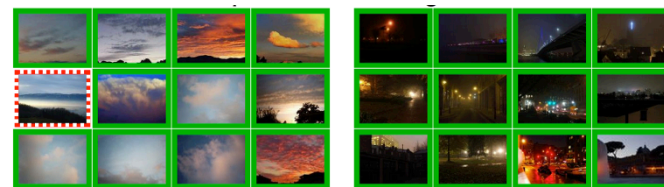
I really enjoyed this film.

Pos+

A complete waste of my time.

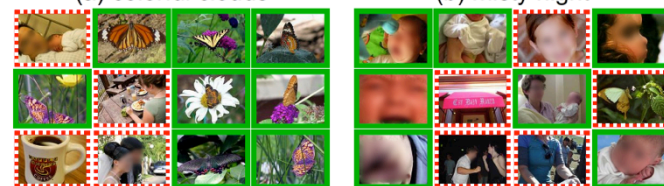
Neg-

Positive Sentiment Negative Sentiment



(a) colorful clouds

(b) misty night



(c) colorful butterfly

(d) crying baby

Sentiment Dataset

Existing image-caption datasets focus on descriptiveness (eg MSCOCO)

Captions are short so we need a compact way of incorporating sentiment

Use **Adjective Noun Pairs (ANPs)**

Collect captions from Amazon Mechanical Turk

Task: Re-write a descriptive sentence using an ANP from a list



Word Pairs

sunny field	good man
good game	beautiful home
great game	clear field
better home	best man
nice man	great ball

1. a man swinging a bat during a baseball game
2. a baseball player bending over to hit a ball
3. a baseball player hitting a baseball at home base

Description

Dataset Validation

Validation: Another AMT task asking if the sentiment is appropriate



The painted train drives through a lovely city with country charm.

The abandoned train sits alone in the gloomy countryside.

A train on the train tracks.

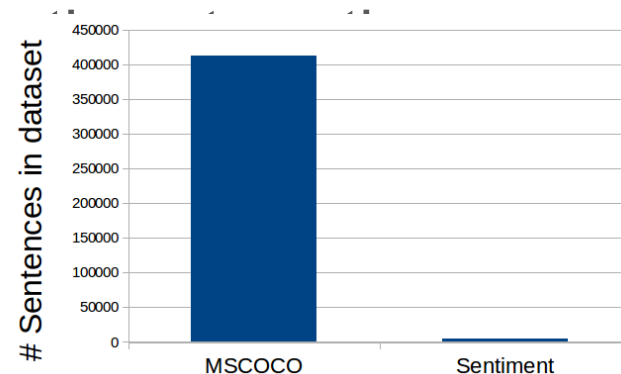
	#imgs	#sentence	descriptiveness	Correct sentiment: #votes			
				3	2	1	0
COCO	124	372	3.42±0.81	355	16	1	0
Pos	124	335	3.34±0.79	315	20	0	0
NEG	123	305	2.69±1.11	250	49	6	0

Incorporating Sentiment: Approach

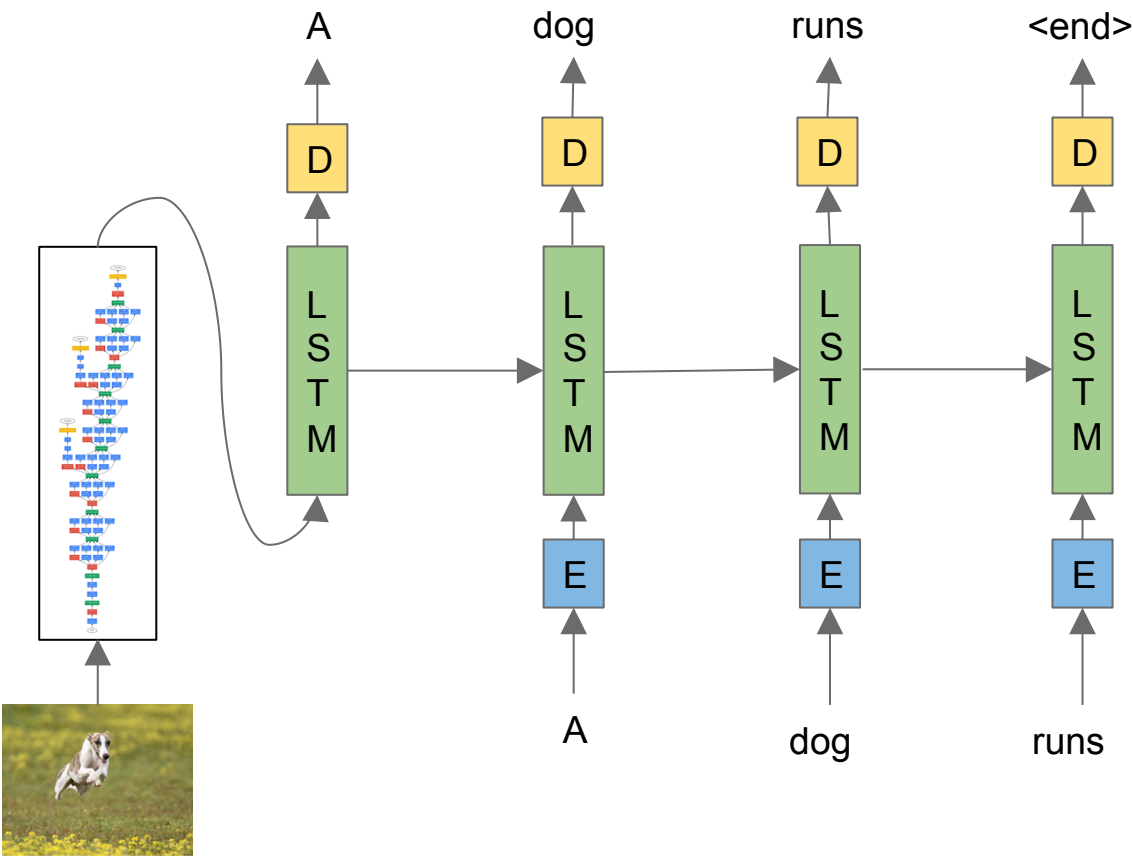
Challenges:

1. Big data + Small data: many descriptive captions, few sentiment captions
2. Generate descriptive captions that **also** have sentiment
3. Identify the important parts of the sentence

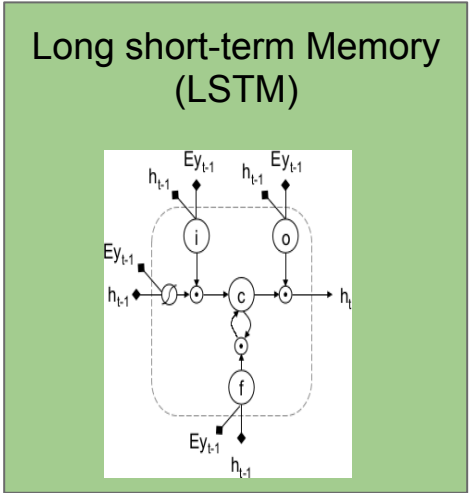
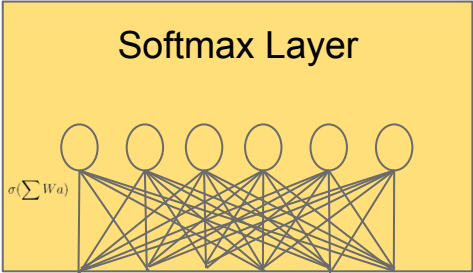
Design a switching RNN that addresses these challenges



Sentence Generation: Recurrent Neural Networks

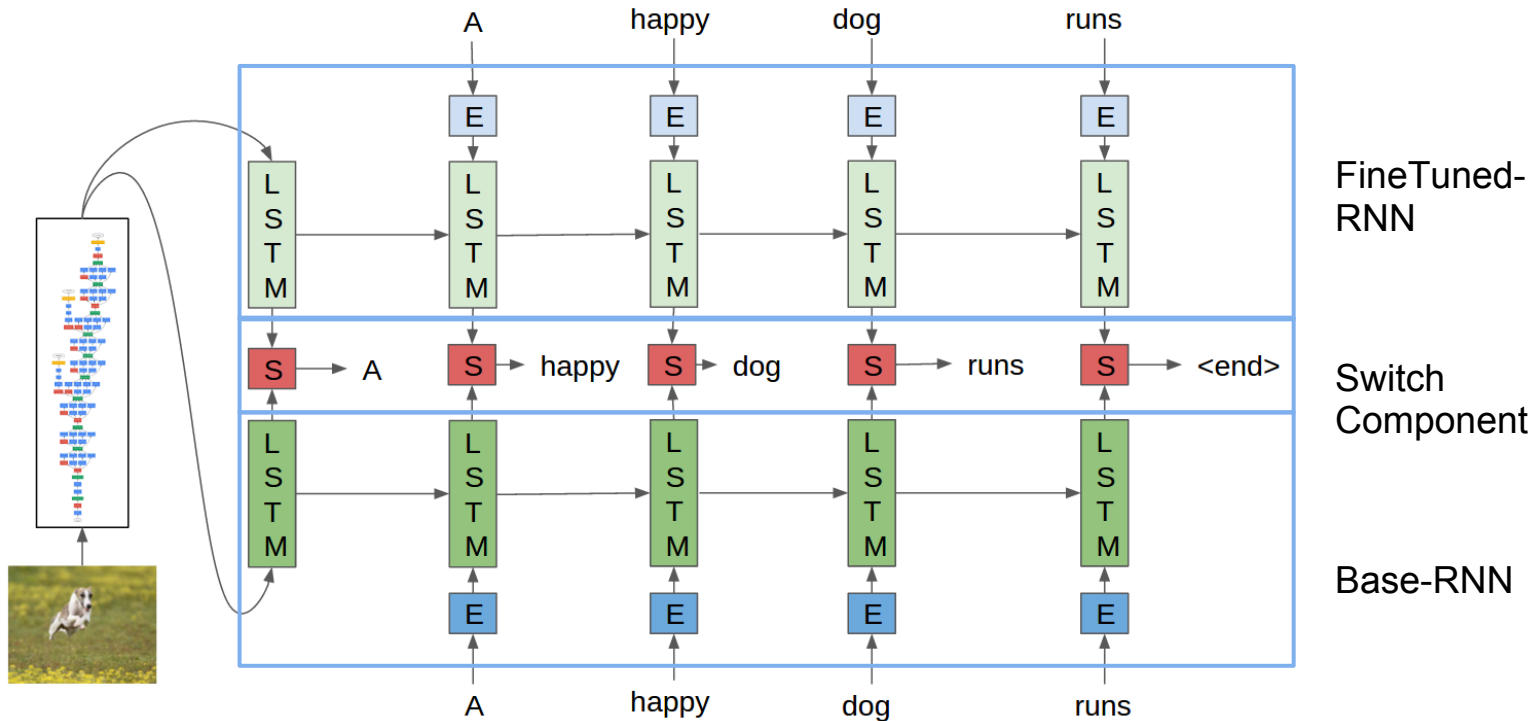


Architecture of:
O. Vinyals and A. Toshev, 2014.



Embedding Layer	
A	0.3, 0.1, 0.2, ...
dog	0.5, 0.7, 0.8, ...
runs	0.3, 0.2, 0.9, ...

SentiCap: Our Model

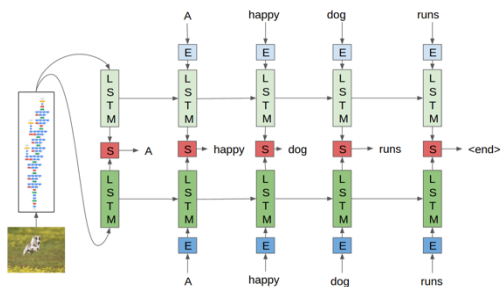


The Base-RNN produces descriptive sentences. (Trained on large data)

The FineTuned-RNN produces captions with sentiment. (Tuned on our dataset)

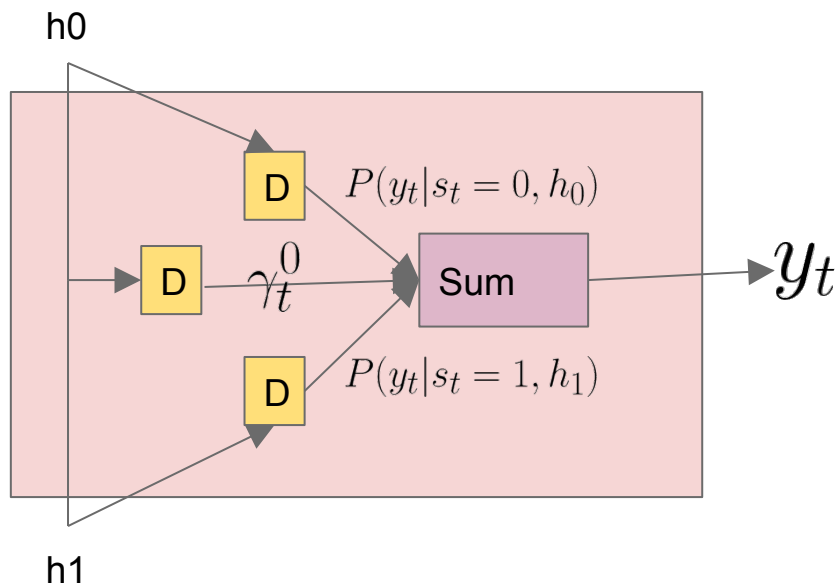
Switch component

Switch Component



$$\gamma_t^0 = \sigma(W_s[h_t^0; h_t^1])$$

$$\gamma_t^0 = P(s_t = 0 | x, y_{1:t-1})$$



γ_t^0 Indicates the presence or absence of a sentiment word.

$$P(y_t | h_1, h_0) = \gamma_t^0 P(y_t | s_t = 0, h_0) + \gamma_t^1 P(y_t | s_t = 1, h_1)$$

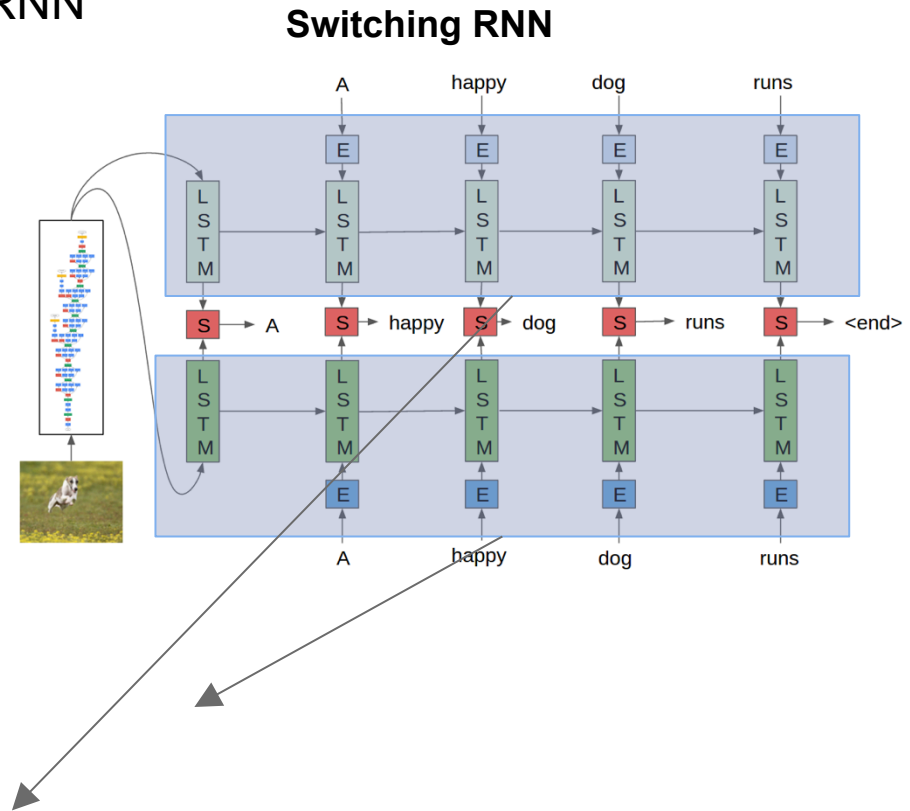
Training Objective

Train the joint model on the sentiment dataset.

- Keep the parameters in the Finetuned RNN “close” to the BaseRNN parameters
- Cross-entropy term ensures:
 - both RNNs are used
 - an increased weight for correctly generating sentiment words

$$\mathcal{L}(\Theta, \mathcal{D}) = - \sum_i \sum_t (1 + \lambda \eta \eta_t^i) [L_t(\Theta, x^i, y^i) +$$

$$\lambda_\gamma (\eta_t^i \log \gamma_t^{1,i} + (1 - \eta_t^i) \log \gamma_t^{0,i})] - R(\Theta)$$



$$R(\Theta) = \frac{\lambda_\theta}{2} \left\| \Theta^1 - \Theta^2 \right\|^2$$

Results: Examples



a great variety of fresh fruits and vegetables



a cuddly cat is laying on a bed



an ugly car is parked in front of an abandoned building



a lonely train pulling into a train station



a delicious piece of cake sitting on top of a white plate



a clock on the side of a beautiful building



a man in a stupid hat is riding on the back of a crazy horse



a silly cat standing in front of a dirty wall

Evaluating the Result

Automatic:

N-gram based metrics: BLEU, ROUGE, METEOR, CIDEr

Human:

Used Amazon Mechanical Turk

- Most positive caption
- Most interesting caption
- How descriptive is the caption

Avoiding poor quality workers

- Reject using average accuracy on human written captions
- More restrictive worker qualifications



Caption	Most positive	More interesting	Describes the image			
			Correctly	Almost	Barely	Unrelated
a group of people on a boat in a body of water	<input type="radio"/>	<input type="radio"/>	<input type="radio"/> 1	<input type="radio"/> 2	<input type="radio"/> 3	<input type="radio"/> 4
a great group of people on a boat in the calm water	<input type="radio"/>	<input type="radio"/>	<input type="radio"/> 1	<input type="radio"/> 2	<input type="radio"/> 3	<input type="radio"/> 4

☐ Sentences are identical

Results

		SEN%	B-1	B-2	B-3	B-4	ROUGE _L	METEOR	CIDE _r	SENTI	DESC	DESCCMP
POS	CNN+RNN	1.0	48.7	28.1	17.0	10.7	36.6	15.3	55.6	–	2.90±0.90	–
	ANP-Replace	90.3	48.2	27.8	16.4	10.1	36.6	16.5	55.2	84.8%	2.89±0.92	95.0%
	ANP-Scoring	90.3	48.3	27.9	16.6	10.1	36.5	16.6	55.4	84.8%	2.86±0.96	95.3%
	RNN-Transfer	86.5	49.3	29.5	17.9	10.9	37.2	17.0	54.1	84.2%	2.73±0.96	76.2%
	SentiCap	93.2	49.1	29.1	17.5	10.8	36.5	16.8	54.4	88.4%	2.86±0.97	84.6%
NEG	CNN+RNN	0.8	47.6	27.5	16.3	9.8	36.1	15.0	54.6	–	2.81±0.94	–
	ANP-Replace	85.5	48.1	28.8	17.7	10.9	36.3	16.0	56.5	61.4%	2.51±0.93	73.7%
	ANP-Scoring	85.5	47.9	28.7	17.7	11.1	36.2	16.0	57.1	64.5%	2.52±0.94	76.0%
	RNN-Transfer	73.4	47.8	29.0	18.7	12.1	36.7	16.2	55.9	68.1%	2.52±0.96	70.3%
	SentiCap	97.4	50.0	31.2	20.3	13.1	37.9	16.8	61.8	72.5%	2.40±0.89	65.0%

Automatic Evaluation:

- sentences are similar to those in the sentiment dataset

Human Evaluation:

- sentences express stronger sentiment according to human evaluators

Summary

1. Introduced the task of generating image captions with sentiment
2. Constructed a dataset of image sentiment caption pairs
3. Designed a switching RNN model which:
 - a. Generates image descriptions
 - b. Uses a large descriptive dataset and a small sentiment dataset for training

A first step towards more natural and more interesting captions

Future: more fine-grained sentiments

Our dataset is available at:

[http://
users.cecs.anu.edu.au/
~u4534172/senticap.html](http://users.cecs.anu.edu.au/~u4534172/senticap.html)

Thank You.