Generating Diverse and Descriptive Image Captions Using Visual Paraphrases Supplementary Material

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1. More Examples

In this supplementary material, we report more examples in MS COCO dataset Karpathy test split for qualitative analysis. Detailed descriptions of the images in generated captions are emphasized with different colors, which may reflect diversity and descriptiveness.

We first show examples in Figure 1 to compare captions generated by different scoring functions (**Ours (len, 0)**, **Ours (Yngve, 0)**, **Ours (IR, 2)**, and **Ours (Tdiv, 0.3)**), along with captions generated by **Attention** baseline. As is shown, captions generated by **Ours (len)** indeed describe more details, but tend to be very long, sometimes truncated due to the length limitation (in Figure 1(c)). **Ours (Yngve)** also captures some important details, but still lacks in diversity of wordings and expressions. Captions by **Ours (IR)** may miss some details, but overall they are concise and precise descriptions. **Ours (Tdiv)** provides precise and natural image descriptions with both rich expressions (such as *"a scenic view"* in (b)) and descriptive details (such as *"with people loading off"* in (c)).

Example images with captions generated in both two decoding steps of **Ours (IR, 2)** and **Ours (Tdiv, 0.3)** are shown in Figure 2, with obvious difference between outputs from the two steps to be found. Compared to the captions generated in the first decoding step, the final captions are usually longer and better with more details (such as *"a catcher and umpire behind him"* in Figure 2(b) and *"next to a railroad crossing"* in (c)) and polished expressions (such as *"a surfer"* instead of "a man" or "a person" in (a)), thus are more diverse in wordings and expressions and more descriptive with respect to important details.

More examples of **Ours (Tdiv, 0.3)**, **Ours (IR, 2)**, and baseline methods including **Attention**, **GAN** and **StackCap** are shown in Figure 3. Comparing to baselines, our models especially **Ours (Tdiv)** perform well in most cases. However, it is worth pointing out that mistakes may come along with more detailed descriptions (such as *next to a american flag* in Figure 3(c), where an improper preposition and a wrong article are used). Moreover, Figure 3(f) shows a failure case when dealing with very complex images, both our models and other baseline models are struggling to make a description on the whole, while humans can usually find some way to summarize in a sentence with reasoning based on commonsense knowledge.

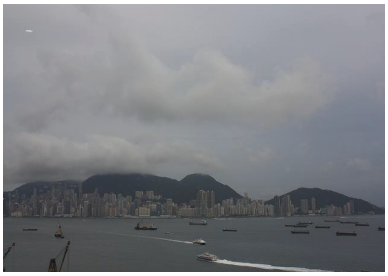
2. Human Evaluation Details

In human evaluation, We compared methods on 100 images randomly sampled from Karpathy test set. Volunteers are asked to compare 9 sentences from 9 models to rate them from the 1-5 scale. The definitions of four criteria of human evaluation are:

- Relevance: whether the sentence correctly describes the visual content and be closely relevant to the image.
- Fluency: whether the caption is a fluent sentence.
- Diversity: whether the sentence uses diverse expressions. If it only uses very simple and ordinary expressions then it should receive a low score.
- Descriptiveness: whether the sentence is an precise, informative caption that describes important details of the image.

(a)

Attention: a woman standing in front of a brick building
Ours (len): a woman in a yellow jacket holding a red umbrella in front of a building
Ours (Yngve): a woman standing in front of a brick wall holding a red umbrella
Ours (IR): a woman in a yellow coat holding an umbrella
Ours (Tdiv): a woman in a yellow jacket holding an umbrella in front of a brick building
Human: a woman in a yellow coat uses a red umbrella to shield herself from the rain



(b)

Attention: a large body of water with lots of boats
Ours (len): a large body of water with boats in the water and a building in the background
Ours (Yngve): a large body of water with boats in the water and buildings in the background
Ours (IR): boats in a harbor with a city in the background
Ours (Tdiv): a scenic view of a harbor with boats in the water and mountains in the background
Human: a picture of some boats and cityscape on a cloudy day

(c)

Attention: a white and blue airplane parked on a runway
Ours (len): a large passenger jet sitting on top of an airport tarmac with people in the
Ours (Yngve): a large white and blue jet airliner on runway
Ours (IR): a large white and blue airplane on a tarmac
Ours (Tdiv): a large white and blue jet airliner on the tarmac with people loading off it
Human: a large plane with people alighting at the airport

Figure 1. Examples of captions generated by Attention baseline and our models using different scoring functions.

(a)

Attention: a man riding a wave on top of a surfboard
Ours (Tdiv, first): a person riding a surf board on a wave
Ours (Tdiv, second): a surfer in a wet suit riding a wave on a surfboard
Human: A person wearing a black water suit surfs in the ocean

(b)

Attention: a baseball player swinging a bat at a ball
Ours (Tdiv, first): a baseball player swinging a bat at a ball
Ours (Tdiv, second): a baseball player swinging a bat at a ball with a catcher and umpire behind him
Human: an umpire officiates a game of little league baseball

(c)

Attention: a stop sign with a stop sign on it
Ours (IR, first): a stop sign that is on the side of a pole
Ours (IR, second): a red stop sign sitting next to a railroad crossing
Human: a red stop sign covered in graffiti under a train crossing

Figure 2. Examples of captions generated in two decoding steps of our models.

(a)

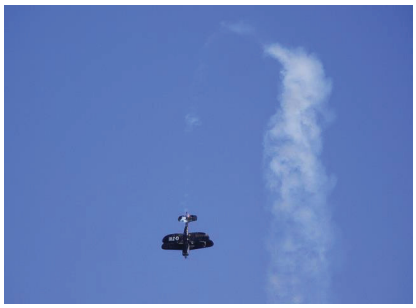
Attention: a small wooden house with a train on the tracks
GAN: an old wooden bench in the middle of the park
Stack-Cap: a red stop sign sitting on top of a bench
Ours (IR): a model train station with a train and a train
Ours (Tdiv): a model train station with a small model train on the tracks
Human: a very nice looking train set with some pretty scenery

(b)

Attention: a green plant is hanging from a tree
GAN: there is an image of a flower in a large tree
Stack-Cap: a plant with a bunch of green bananas
Ours (IR): a bunch of bananas hanging from a tree
Ours (Tdiv): a banana tree with a bunch of bananas hanging from it
Human: a bunch of bananas are hanging from the banana tree

(c)

Attention: a red fire truck driving down a street
GAN: the fire truck is painted red and red fire truck
Stack-Cap: a fire truck is driving down a city street
Ours (IR): a red fire truck driving down a street
Ours (Tdiv): a red fire truck driving down a street next to a american flag
Human: a fire truck with some flags going down the road



(d)

Attention: an airplane flying in the sky with a blue sky
GAN: an airplane flying high in the sky over the clouds
Stack-Cap: a plane is flying in the blue sky
Ours (IR): a plane flying in a clear blue sky
Ours (Tdiv): an airplane flying in the sky with a trail of smoke coming out of its back
Human: A prop plane is flying through the sky

(e)

Attention: a vase filled with flowers on a table
GAN: there is a vase filled with flowers on a table in a vase
Stack-Cap: a vase with flowers in it on a table
Ours (IR): a vase filled with red flowers on a table
Ours (Tdiv): a glass vase filled with red and white flowers on a table
Human: white and orange flowers in a glass vase

(f)

Attention: a blue umbrella sitting on the side of a building
GAN: an umbrella decorated with an umbrella in front of an umbrella
Stack-Cap: a blue umbrella sitting on top of a table
Ours (IR): a colorful umbrella sitting in the middle of a mall
Ours (Tdiv): a colorful umbrella is hanging from the ceiling of a building
Human: row of umbrellas of various colors under a pavilion

Figure 3. More qualitative examples of different baselines and our models.