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Image Captioning using pre-trained GPT-2 models

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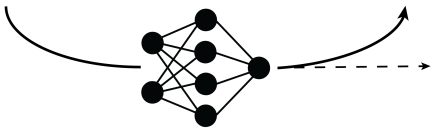
Introduction

For describing the image you will need to know:

- What everything is?
- Where is it?
- What is it doing?
- What is important to describe?
- Objects/colors/positions/relationships

. . .

Generated captions:
A group of kids pose in front of a pizza.
A team of pizza makers holding a fresh pizza.
Three people pose for the camera while holding a pizza.



- **Computer vision:** recognize objects.
- **Natural Language Processing:** generate fluent description.

Motivation and objectives

Applications of image captioning

- Image indexing
- Help for visually impaired people
- Medical image understanding
- Social Media

Problems in image captioning

- Object Hallucination: recognizing objects that are not in the scene.
- Exposure Bias Problem: LM models guess the next word based on the ground truth's previous words.

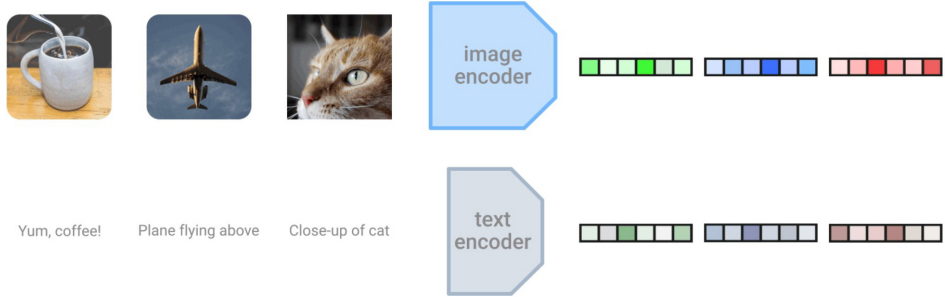
Objectives

1. Implement several strategies to improve the state of the art image captioning models.
   - Tackle the Exposure Bias Problem
   - Tackle the Object Hallucination problem
2. Study the state of the art models in image captioning.

State of the art

Computer vision

1. **Convolutional Neural Networks (CNN)** (LeCun et al., 1989)
2. **Vision transformers** (Dosovitskiy et al., 2020)
3. **Contrastive Language–Image Pre-training (CLIP)** (Radford et al., 2021): The model learns to associate each image with its text companion, while dissociating it from the other texts.



Images source: https://ai.googleblog.com/2022/04/locked-image-tuning-adding-language.html

State of the art

Language models

Objective: estimate the probability distributions of words in a vocabulary given a sequence of context words.

$$\mathrm{p}(w_i \mid w_1, \ldots, w_{i-1})$$

Neural network based language models: Recurrent Neural Networks (RNNs), Transformers

State of the art

Language models: Generative Pretrained Transformer 2 (GPT-2)

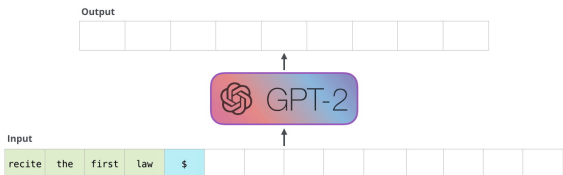
Outputs token probabilities given some context tokens

$$\mathrm{p}(w_i \mid w_1, \ldots, w_{t-1}), \quad i = 1, \ldots, |V|$$

model vocabulary size
50,257

0.19850038	aardvark
0.7089803	aarhus
0.46333563	aaron
	…
	…
	…
	…
	…
-0.51006055	zyzzyva

GPT-2 (Radford et al., 2019) is an autoregressive model:



Images source: https://jalammar.github.io/illustrated-gpt2/

Decoding methods:

- Greedy search: chooses the word with the highest probability.

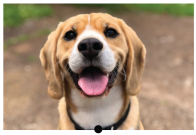
$$w_t = \arg\max_w \mathrm{p}(w \mid w_1, \ldots, w_{t-1})$$

- Beam search: keeps N hypotheses and selects the one with the greatest probability.

Image Captioning

State of the art architectures

CNN-based

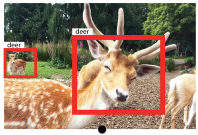


CNN

LM
e.g. Transformer, RNN

"A happy dog smiling"

Object detection + CNN



Object detector

CNN

LM
e.g. Transformer, RNN

"A happy deer standing in a field"

Pretrained Language Models

CLIP

Mapping Network

prefixes

Pretrained LM
e.g. GPT-2, GPT-3

"A picture of a sweet pangolin"

Experimental framework

Dataset

MSCOCO dataset (Lin et al., 2014)

1. 120K images, 5 captions per image
2. Human-curated captions
3. 80 categories of images

Karpathy splits (Karpathy and Fei-Fei, 2015):

118,000	5,000	5,000
Training	Validation	Test

A woman sitting at a desk in her work station.

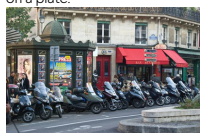
A pair of pizza rolls for sale are on a plate.

A dog holding a yellow frisbee in it's mouth.

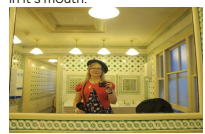
Sheep are separated in stalls two by two.

A red stop sign sitting in the middle of a street.

A very long sandwhich on a table.



Many small motorbikes are parked along the street.



A woman taking a selfie in front of a large mirror.

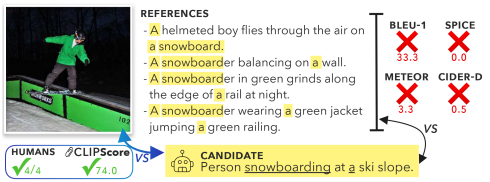
Two people use surfboards on a wave in the ocean.

A man pushes a cart with wheels with bananas.

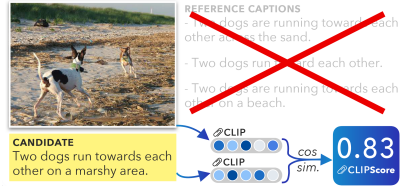
Experimental framework

Metrics

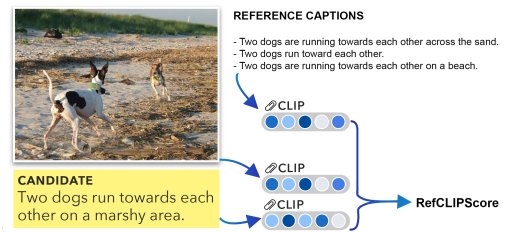
Reference based: `BLEU, METEOR, ROUGE, CIDER, SPICE`



Reference free: `CLIPScore`



Reference free + Reference based: `RefCLIPScore`



Images source: Hessel et al., 2021

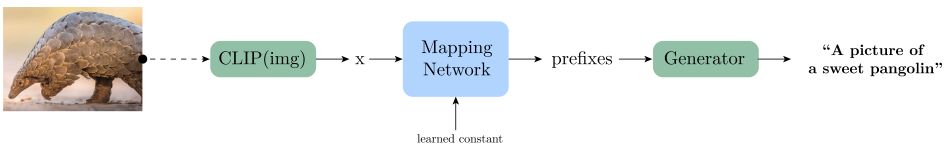
Experimental framework

Proposals

1. **CNN + Transformer.** The following CNNs are used:
   - EfficientNetB0 (Tan and Le, 2019).
   - VGG16 (Simonyan and Zisserman, 2014).
   - ResNet50 (He et al., 2016).

2. **Modifications on the ClipCap framework (Mokady et al., 2021)** to improve the generated caption by taking into account the CLIPScore metric during inference.

   Idea: By improving the captions using the CLIPScore metric, **the final caption will better describe the input image.**



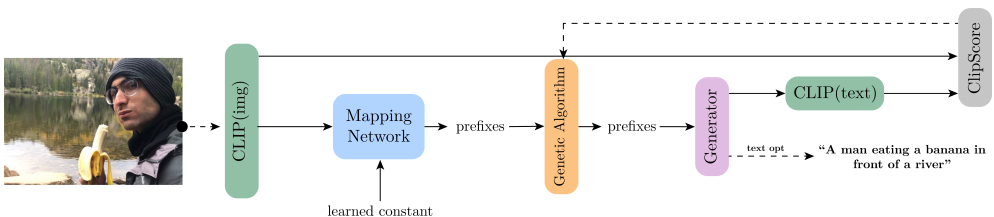
Experimental framework

Proposals: Genetic

The Transformer model outputs a set of vectors (*prefixes*) that tame the language model (GPT-2).

Idea: by optimizing the CLIPScore metric during inference, those prefixes can be enhanced and therefore, the candidate caption can be improved (based on Galatolo et al., 2021).

→ A Genetic Algorithm is used to optimize the prefixes by maximizing the CLIPScore metric.



Experimental framework

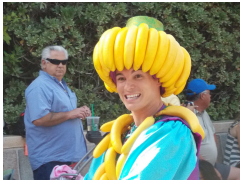
Proposals: Max Similarity

candidate caption

CLIP visual embedding

$$\max_{h \in H} \text{CLIP-S}(h, v)$$

set of hypotesis



H = { "A person wearing a banana headdress and necklace",
"A lady dressed in a blue and purple outfit wearing a hat made of fruit.",
"A person wearing a hat made out of yellow bananas.",
"Person with bananas on head and banana necklace.",
"A woman wears a hat that is made of bananas" }

- Beam search generates N candidate captions
- The candidate caption with the highest CLIPScore metric is chosen

N is a **hyperparameter**!

Experimental framework

Proposals: Greedy search based on CLIPScore

Greedy search: $w_t = \underset{i=1,\ldots,|V|}{\arg\max}\ \mathrm{p}(w_i \mid w_1, \ldots, w_{t-1})$

Proposed idea: select the next word that maximizes a linear combination between CLIPScore and the conditional probability $\mathrm{p}(w_i \mid w_1, \ldots, w_{t-1})$.

$$w_t = \underset{i=1,\ldots,N}{\arg\max}\ \beta\ \mathrm{p}(w_i \mid w_1, \ldots, w_{t-1}) + (1-\beta)\ \frac{1}{2.5}\ \texttt{CLIP-S}_i$$

Results

Comparison of models

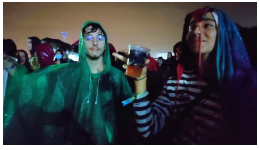
Results of the Karpathy split for several image captioning frameworks:

Model	METEOR	CIDEr	SPICE	CLIP-S	CLIP-S^{ref}
VinVL (Zhang et al., 2021)	**0.311**	**1.409**	**0.252**	0.760	0.820
tewel2021zero (Tewel et al., 2021)	0.115	0.146	0.055	**0.870**	0.790
CLIP-VL (Shen et al., 2021)	0.297	1.342	0.238	0.770	0.820
ClipCap (Mokady et al., 2021)	0.271	1.083	0.201	0.770	0.810
Ours; Genetic	0.225	0.696	0.164	0.814	0.827
Ours; Greedy Search	0.207	0.618	0.145	0.845	**0.842**
Ours; Max Similarity	0.260	0.932	0.197	0.799	0.830
Ours; VGG + Transformer	0.208	0.672	0.135	0.657	0.722
Ours; ResNet + Transformer	0.218	0.732	0.146	0.677	0.739
Ours; EfficientNetB0 + Transformer	0.228	0.807	0.159	0.700	0.759

Table: Comparison of models. We report supervised metrics (those that require human references): METEOR, ROUGE, CIDEr, SPICE. Finally, we report semantic relatedness to the image (CLIP-S), and to the human references (RefCLIPScore) based on CLIP's embeddings.

Results

Image examples



Beam search	A group of people with umbrellas in the air.	A man standing next to a woman holding a phone.	A group of people sitting next to a statue of a basilisk.
Greedy Search	A group of drinking fans outside a festival.	A couple of people holding hands talking on a political crisis.	A Christmas tree with a man and a woman reading a book.
Genetic	A group of people with different colors and sizes of glass bottles in the rain.	A picture of two people standing next to each other in a room.	A young boy reading a book in front of a statue of a man in a christmas costume.
Max Similarity	A group of people with umbrellas and a jug of water.	A man standing next to a woman holding a phone.	A group of people sitting next to a statue of a teddy bear.
EfficientNet + Transformer	A woman is holding a cell phone in her hand.	A man in a red shirt and a red tie.	A woman sitting on a bench with a cell phone.
VGG + Transformer	A woman is holding a cell phone to her ear.	A man in a suit and tie holding a cell phone.	A group of people sitting around a table with a cake.
ResNet + Transformer	A woman and a man are holding a wii remote.	A man and a woman are holding up a kite.	A woman and a man standing in front of a christmas tree.

Results

Textual cues: Adversarial pixel perturbations

Greedy Search
$\beta = 0.05$ $N = 30$

A boat owned by a criminal is at the bank of a harbor.

A white boat parked in a dock with a railing.

Conclusions and future work

Conclusions

- We have intoduced novel methods that improve the generated caption by using the CLIPScore metric. Objective 1
  - The Object Hallucination problem and the Exposure Bias Problem can be tackled by using the proposals based on improving the generated caption in testing time. Sub-objective 1
- Proposed methods outperformed the state of the art models in the RefCLIPScore metric.
- Several state of the art techniques to tackle image captioning have been reviewed. Objective 2

Future work

- Explore other pre-trained language models such as GPT-3 (Brown et al., 2020), GATO (Reed et al., 2022), Flamingo (Alayrac et al., 2022), etc.
- Determine whether the models have any biases.

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Questions?

Javier Garcia Gilabert

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