Storyteller

From images to stories

Mingfei Cui, Silvia Cardani 31.1.2023

LMU – WS2022/2023 – Seminar Computational Creativity, Prof. P. Wicke

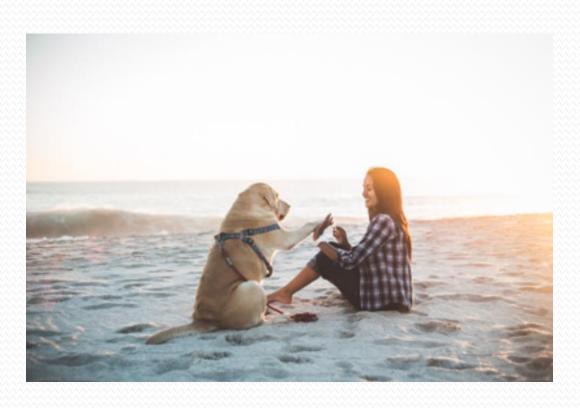
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Motivation and first steps

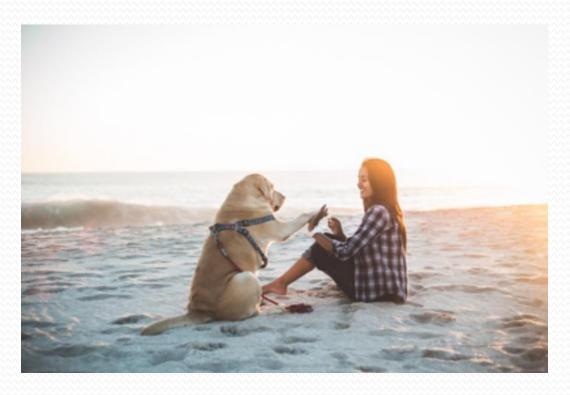
- ➤ Building a model that from a sequence of images is able to generate a short story in a certain framing
- ➤ Several pre-existing image-captioning models based on COCO caption dataset were tested to choose the best one. Some of them: Grit, Oscar, Xmodal-Ctx, Meshed-Memory Transformer, OFA, BLIP, Lavis (that integrates BLIP)
- 1. The original models were first run to check their functionality
- 2. then a new image was used as input and the code was adapted
- Basing on the results (quality of the caption obtained), BLIP was chosen

OFA – test result



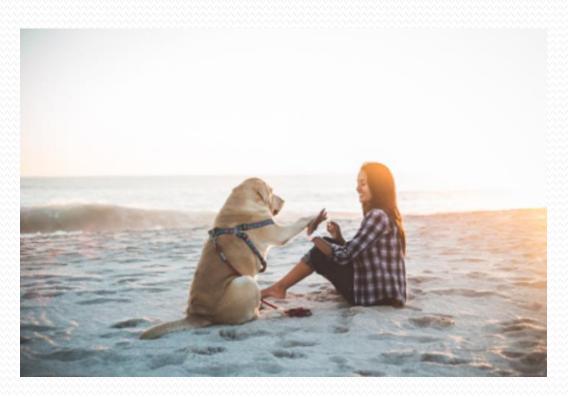
Generated caption: "a woman and a woman sitting on the beach in front of the ocean"

BLIP – test result



Generated caption: "a woman and her dog on the beach"

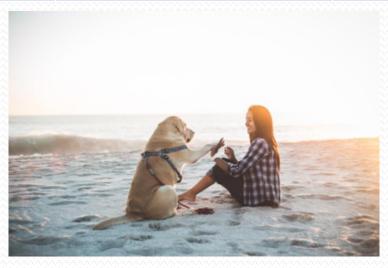
LAVIS (with BLIP) – test result



Generated caption: "there is a woman sitting on the beach with her dog"

Test result comparison

OFA	BLIP	LAVIS (with BLIP)
"a woman and a woman sitting on the beach in front of the ocean"	"a woman and her dog on the beach"	"there is a woman sitting on the beach with her dog"



Storyteller

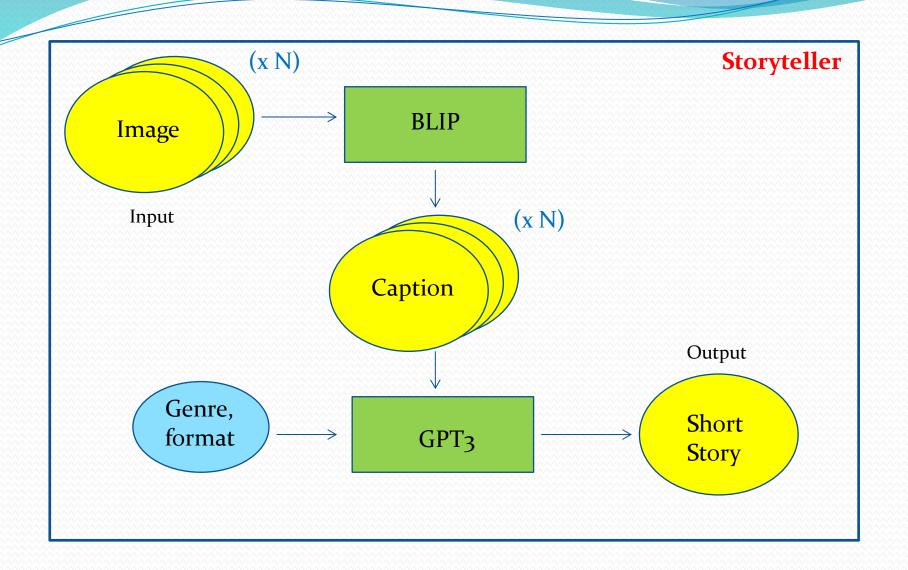
In Storyteller, the generation of a short story is done in several steps:

- uploading a sequence of images as input
- 2. random *generation of captions* for the images
- *a story is output* using these captions

Architecture of Storyteller

Storyteller is made of different parts, reflecting the image-totext generation process:

- *BLIP* (Bootstrapping Language-Image Pre-training) is first used to generate captions for the prompted images
- *GPT*₃ (Generative Pre-trained Transformer 3) is then employed to generate a story by using Text Completion, basing on the captions generated by BLIP and on the user's choice of the story's genre and format



Architecture of Storyteller

BLIP

BLIP: Bootstrapping Language-Image Pre-training for Unified Vision-Language Understanding and Generation

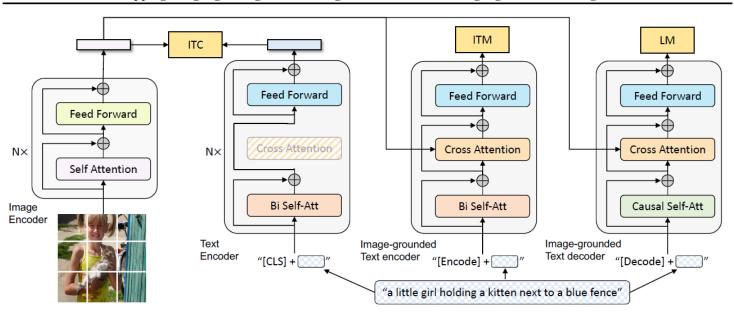


Figure 2. Pre-training model architecture and objectives of BLIP (same parameters have the same color). We propose multimodal mixture of encoder-decoder, a unified vision-language model which can operate in one of the three functionalities: (1) Unimodal encoder is trained with an image-text contrastive (ITC) loss to align the vision and language representations. (2) Image-grounded text encoder uses additional cross-attention layers to model vision-language interactions, and is trained with a image-text matching (ITM) loss to distinguish between positive and negative image-text pairs. (3) Image-grounded text decoder replaces the bi-directional self-attention layers with causal self-attention layers, and shares the same cross-attention layers and feed forward networks as the encoder. The decoder is trained with a language modeling (LM) loss to generate captions given images.

BLIP

- First a *Visual Trasformer* dividing the input image into patches and encoding them as embeddings
- Then, Multimodal mixture of Encoder/Decoder:
- 1. BERT-based *Text Encoder*, to align the two feature text and image in the semantic space (input: image/text pair)
- 2. Image-grounded Text Encoder, to capture the fine-grained grounded alignment between vision and language. It predicts the match positive and unmatch negative pair, acting as a filter
- Jamage-grounded Text Decoder, to predict the next token. The image-grounded text decoder is activated to generate textual descriptions given an image

BLIP

- To perform efficient pre-training, the encoder employs bidirectional self-attention to build representations for the current input tokens
- The *decoder* employs *causal self-attention* to predict the *next* tokens
- CapFilt: Captioner + Filter to improve the quality of the text corpus, as noisy data (wrong description of images) affects the learning of the vision-language alignment signal. They are fine-tuned individually on the high quality human-annotated COCO dataset. Bootstrapping is performed
- *Nucleus sampling* was chosen as a sampling method, instead of beam search, for larger variety and better creativity

LAVIS (with BLIP) – Nucleus sampling example



Multiple captions generated with nucleus sampling:

- "a cat is on its back playing with a Christmas tree"
- 2) "an orange cat reaching up to a Christmas tree"
- 3) "a cat on a tree with an orange Christmas star"

BLIP – effects of CapFilt



T_w: "from bridge near my house"

 T_s : "a flock of birds flying over a lake at sunset"



Human caption:

T_w: "in front of a house door in Reichenfels,
Austria"

Synthetic caption:

T_s: "a potted plant sitting on top of a pile of rocks"



T_w: "the current castle was built in 1180, replacing a 9th century wooden castle"

 T_s : "a large building with a lot of windows on it"

Figure 4. Examples of the web text T_w and the synthetic text T_s . Green texts are accepted by the filter, whereas red texts are rejected.

Synthetic texts produced by CapFilt are often more precise than human descriptions of images found in the web

GPT3

- Very large Transformer model from OpenAI, with 175 billions parameters
- Trained using the following datatsets: Common Crawl, WebText2, Books1, Books2, Wikipedia
- After training GPT3, a task description, eventual examples and a prompt are input to get a prediction
- In the training the model should have seen the same structure and somehow match the pattern
- The model returns a Text Completion in natural language (predicts the next most likely word)

Transformer

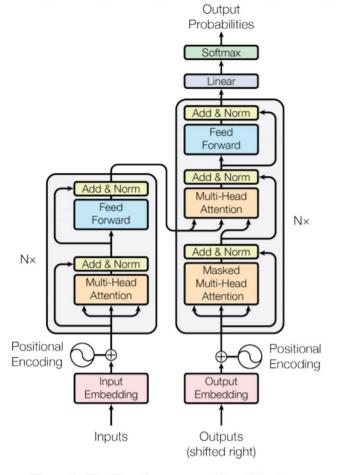


Figure 1: The Transformer - model architecture.

GPT3 as a Transformer

- *Positional Encoding*: to encode the position of the current token in the sequence
- *Multi-head Attention*: predicts which input tokens to focus on and how much. E.g. in a sequence of 3 tokens, weight matrices are learnt. These transform our sequence embeddings into 3 separate 3x64 matrices, each one for a different task. The first 2 matrices (queries and keys) are multiplied together, which yields a 3x3 matrix. This matrix (normalized through softmax) represents the importance of each token to each other tokens. This is then multiplied with the third matrix (values), giving, for each token, a mix of all other token values weighted by the importance of their respective tokens. The process is repeated 96 times in GPT-3

GPT3 as a Transformer

- Feed forward: a multi-layer-perceptron (the input is multiplied with learnt weights, learnt bias is added) with 1 hidden layer
- Decoding: After passing all the 96 layers of GPT-3, the start encoding mapping (word to vectors) is reversed to transform our output vector embedding back into a word encoding

GPT3: Parameters

- *Model*: engine employed to generate predictions
- Max_tokens: max nr. of tokens generated by the model
- *Temperature*: to control randomness and creativity of the model. Before applying softmax, output values can be scaled with temperature. If close to 1, no values modifications happen before softmax. If close to 0, the model becomes more deterministic, outputting the same tokens after a given sentence (highest probable token will become very likely)
- Frequency_penalty: controls the model's tendency to repeat predictions. It reduced the probabilities of words that have already been generated, depending on their frequency. Default is o

GPT3: Parameters

- Presence_penalty: encourages the model to make new predictions. It lowers the probabilities of a word if it already appreared in the prediction, not depending on frequency. Default is o
- Top_p: also nucleus sampling, the sampling threshold during inference time. It limits the amount of possible words to sample in the output to the k most likely predicted words. E.g. with a top-k parameter of 1 (neuter), it always picks the most likely word. If set e.g. to 3.5%, the model will sample and select randomly among the objects in their cumulative distribution of 3.5%, according to their likelihood (e.g. one 2%, the other 1.5%). This also controls originality and randomness. OpenAI recommends to variate either top_p or temperature and leave the other at 1

Features of Storyteller

Storyteller:

- friendly introduces itself to the user
- lets the user choose the images for the story
- also lets choose the genre and the format of the story
- is able to *recognize typing errors*, so that the user can correct them. This refers to the number of images, genre and format
- If the user is not satisfied with the story proposed, he/she can make the system generate other stories

Choice of genre and format

To diversify genre and format of the story, Storyteller gives the user the following possibilities:

- For category Book:
 - Lord of the Rings
 - Harry Potter
- For category *TV-show*:
 - Sitcom
 - Doctor Who
 - Stranger Things
- For category *Play*:
 - Shakespeare
 - West End Musical
 - Pantomime

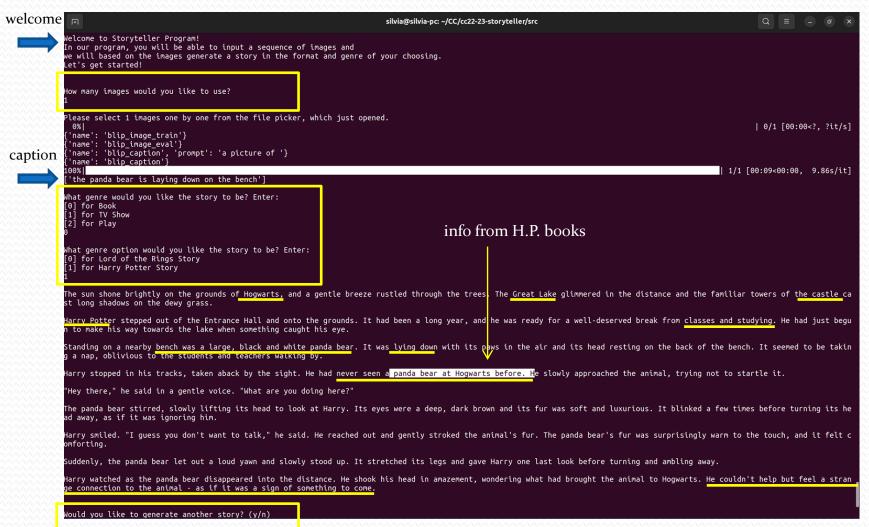
Output examples: Input Images



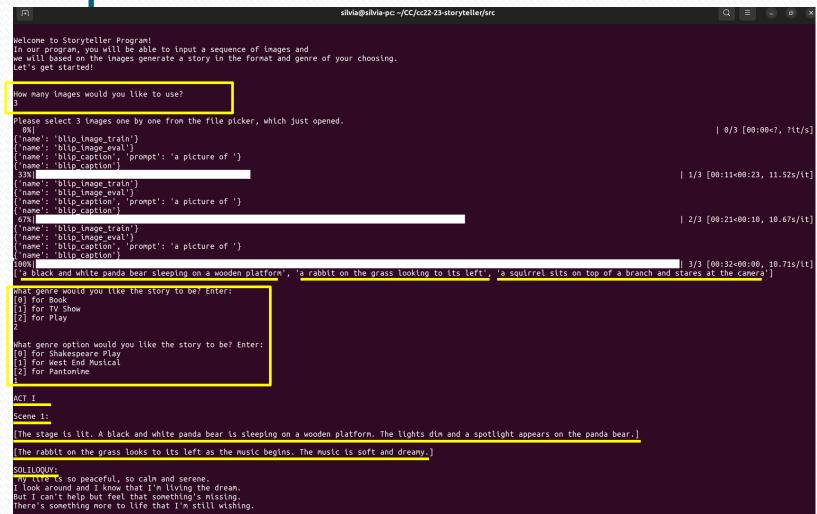




Output ex. 1: Harry Potter Book

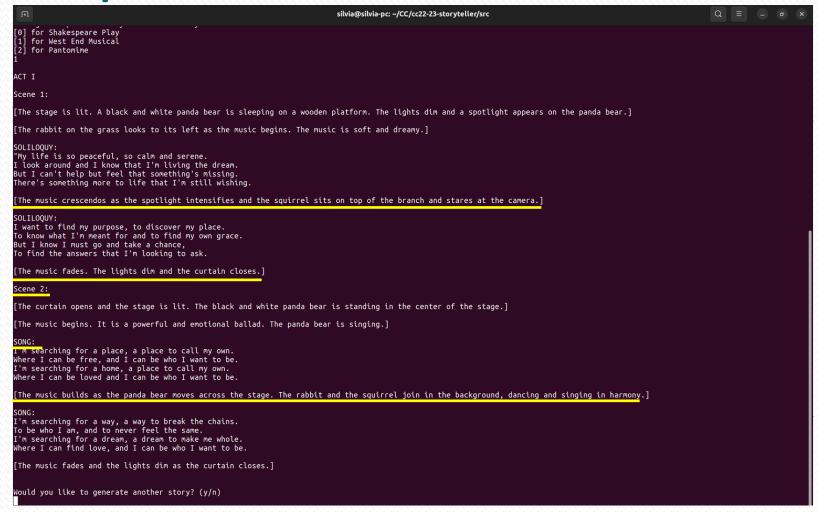


Output ex. 2: West End Musical

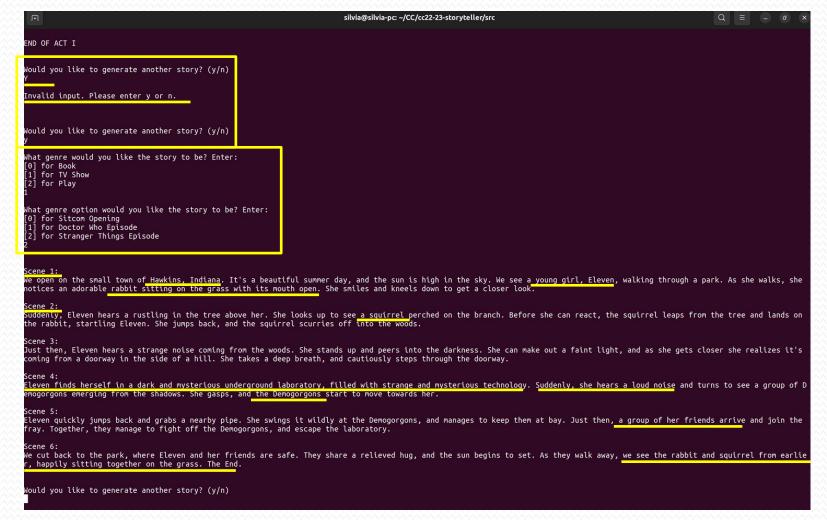


captions

Output ex. 2: West End Musical



Output ex. 3: Stranger Things



Conclusion

- Storyteller can generate a story from images, letting the user select genre and format
- By modifying GPT3 parameters like temperature or top_p (nucleus sampling), the model can become more creative, generating more diverse words in the text
- Using frequency_penalty and presence_penalty can also lead to less repetition in the output

Bibliography

- Li et al., BLIP: Bootstrapping Language-Image Pre-training for Unified Vision-Language Understanding and Generation, arXiv: 2201.12086v2, Feb. 2022
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- 3. Vaswani et al., Attention is all you need, arXiv:1706.03762v5, Dec. 2017 (Tranformers)