

EECS595 Final Project Report Group 10

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Abstract

Image-to-Text is a common Vision-Language Task. Conversely, we have Text-to-Image tasks, which is helpful in data generation and can provide creative ideas. In our project, we tried to combine these two tasks together, to propose a feasible method of generating a suitable dataset for vision-language tasks such as Image Captioning, and to learn about different Image2Text models' performance in predicting the images created by Text2Image tools. We paid attention to one of the most popular image generators Midjourney AI recently, and some vision-language models(mPLUG, OFA). We will compare the models and utilize these tools to generate and analyze our own dataset.

1 Introduction

1.1 Image Captioning

Image-to-Text is a popular technology that converts images to text representations. It requires the vision-language model to extract important features from an image and generate natural language descriptions to accurately describe the content. One of its applications that we will focus on is Image Captioning.

Image Captioning(IC) is one of the most attractive topics in the research area. The objective of image captioning is to solve the semantic gap for computer vision, and allows computers to extract the features from graphics and transfer them to higher-level semantic information. Plenty of previous works showed remarkable developments in IC, and mainstreams for IC include the Transformer-based Encoder-Decoder approach, Attention Mechanism, and some other approaches(Conditional GAN, Reinforcement Learning to improve image captioning, etc.)

It is a challenging problem to achieve end-to-end training for Image Captioning since the visual encoder and language decoder doesn't share the same



Figure 1: midjourney sample

structure (Xu et al., 2022). From a most recent paper using mPLUG that achieves state-of-the-art performance on MS COCO Caption dataset, we were attracted by the unified Multi-modal Pre-training framework named mPLUG, which enables a cross-modal skip-connected network, and allows the fusion of visual and linguistic representations, thus provides an end-to-end model with achieved a high-efficiency performance. With such performance, it is useful on a wide range of vision-language tasks apart from images captioning, such as image-text retrieval and visual question answering(VQA). Similarly, the OFA model uses a Transformer as backbone architecture, and can also achieve high performance on a variety of vision-language tasks. We will mainly compare these two models and test them with the MSCOCO Caption, and the dataset generated by Text2Image generators.

1.2 Text-to-Image

Text-to-Image Tasks involve using text descriptions to generate corresponding images. These tasks are generally performed on Image generators, which are trained on large datasets of images with annotated captions. It covers a large range of applications, including the improvement of image recognition systems and the creation of personalized visual content.

As AI Image Generators becomes popular this year, many practitioners dedicate to grow the capabilities and ease-of-use of their image generator. The Midjourney AI is one of the examples, which is based on a deep generative model to generate images by descriptive text, and makes digital art more accessible to the public with a shareable discord channel. This popular trend arouse our interest in exploring the generated digital images. We wonder would computer recognize AI-generated images easier or harder than real-world images. We considered that Image Captioning is helpful in determining the understanding of the image. Therefore, we decided to use the digital images generated by Midjourney AI as our own dataset, and apply it to the Image Captioning Models such as mPLUG and OFA. After implementing training and fine-tuning, we will evaluate it by comparing the ground-truth image captions (same as the text descriptions we first used to generate our own dataset) with the newly-generated image captions (generated by Image Captioning Models), thus, we can evaluate the results to seek if the Text2Image tool can be helpful in generating fine datasets for visual-language tasks, and further reach a conclusion of computer image recognition system's performance.

2 Previous Work

For the Image Captioning Task, we explore the SOTA models in recent years. Generally, MSCOCO Caption is commonly being used to examine the performance of different models in Image Captioning Tasks. Looking into MSCOCO Captions's benchmark, the mPLUG model and OFA model by Alibaba Group were ranked the highest scores in BLEU-4, CIDEr, METEOR ([Code](#)).

2.1 mPLUG

As shown in Figure 2, mPLUG consists of two uni-modal encoders for image and text independently, a cross-modal skip-connected network, and a decoder for text generation.

First, it uses two unimodal encoders to encode text and images separately. The visual encoder directly applies the transformer on the image patches. The visual encoder encodes the input image patches into a sequence of embeddings $\{v_{cls}, v_1, v_2, \dots, v_M\}$, and the text encoder encodes the input text messages into $\{l_{cls}, l_1, l_2, \dots, l_N\}$. Next, these sequences of embeddings are fed into

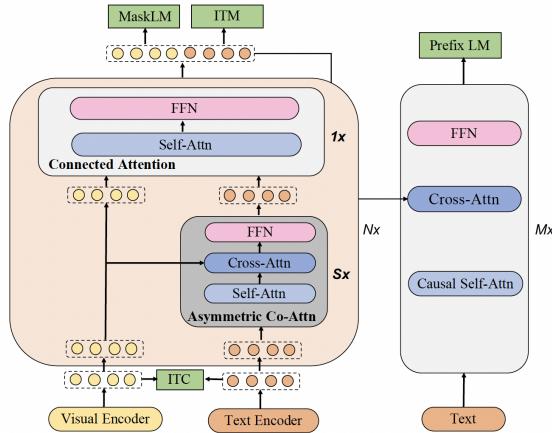


Figure 2: Mplug cross-modal skip-connected network ([Li et al., 2022](#))

a cross-modal skip-connected network, which is used for cross-modal fusion of visual and linguistic representation.

The cross-modal skip-connected network includes multiple skip-connected fusion blocks. For each block, there are S asymmetric co-attention layers and a connected-attention layer. Explicitly, the asymmetric co-attention contains a self-attention (SA) layer, a cross-attention (CA) layer, and a feed-forward network (FFN), using the Linear layer for layer normalization. Once we fed the text feature l^{n-1} to the SA layer, its output will be calculated with the visual feature v^{n-1} in the CA layer, and we will get the visual-aware text representation l^n after passing the FFN. Equations (1) (2) (3) describe the process in the co-attention layer. For connected-attention layer, it is composed of a self-attention layer and a feed-forward network. It takes image feature v^{n-1} and text feature from the co-attention layer as input, and generates visual v^n and linguistic feature l^n as output for the next cross-modal skip-connected network(See equation (4) (5)).

Equations for each Co-Attention layer ([Li et al., 2022](#))

$$l_{SA}^n = LN(SA(l^{n-1}) + l^{n-1}) \quad (1)$$

$$l_{CA}^n = LN(CA(l_{SA}^n, v^{n-1}) + l_{SA}^n) \quad (2)$$

$$l^n = LN(SA(l^{n-1}) + l^{n-1}) \quad (3)$$

Equations for each Connected-Attention layer ([Li et al., 2022](#))

$$[v_{SA}^n; l_{SA}^n] = LN(SA([v^{n-1}; l^{n-1}]) + [v^{n-1}; l^{n-1}]) \quad (4)$$

$$[v^n; l^n] = LN(FFN([v_{SA}^n; l_{SA}^n]) + [v_{SA}^n; l_{SA}^n]) \quad (5)$$

The output of the mPLUG cross-modal skip-connected network is a cross-modal representation, which will be fed into the transformer decoder and implemented with sequence-to-sequence learning to generate the result captions.

2.2 OFA

OFA is proposed with the purpose of achieving an omnipotent model, that is able to unify vision-language, vision-only, and language-only tasks. It is a Task-Agnostic and Modality-Agnostic sequence-to-sequence framework that once reached the state-of-arts in a various number of tasks such as Image Generation, Visual Grounding, Image Captioning, and Image Classification, to name a few. This model uses ResNet modules directly for visual feature extraction and follows the practice of GPT (Alec Radford and Sutskever, 2018), and BART (Mike Lewis and Zettlemoyer., 2020) to process the linguistic information and extract the features from text sequences.

By following the successful multimodal pretraining practices, OFA uses the Transformer encoder-decoder framework as unified architecture for all pretraining, fine-tuning, and zero-shot tasks (Wang et al., 2022). The encoder layer is composed of self-attention layer and a feed-forward network. The decoder layer consists a self-attention layer, a feed-forward network, and a cross attention for connecting the encoder's output and decoder together. Besides, OFA adds more implementations to improve its performance, such as stabilizing training and accelerating convergence. To reach the model's unification, it represents data of various modalities in a unified space and uses a unified vocabulary for all visual and linguistic representations.

2.3 Other Previous Works of Vision-Language Pre-training

Some other previous related works also achieved enormous success in Vision-Language Pre-training(VLP), such as CLIP(Alec Radford), OSCAR(Li et al., 2020), and VinVL (Zhang et al., 2021). According to the paper of mPLUG (Li et al., 2022), the typical approaches to VLP could be approximately divided into two types: dual encoder and fusion encoder. Dual encoders such as CLIP use two single-modal encoders for image and text separately and then apply straight-forward

functions (dot product for example) to model the cross-modal interactions between them. This approach can achieve quite a computation efficiency as the image and text can be pre-computed and cached, however, they might fail for more complicated reasoning tasks such as visual question answering. Another approach, fusion encoder (OSCAR for example), is able to deal with complex reasoning tasks by utilizing deep fusion functions such as multi-layer self-attention or cross-attention networks.

From the Evaluation Results on the COCO caption (Figure 3), based on the same CIDEr Optimization approach, mPLUG has the highest score on BLEU-4, METEOR, and CIDEr than other models. mPLUG uses a visual transformer, which allows the model to be more computationally-friendly than using a pre-trained object detector to extract visual features of image patches. It also addressed the problem of information asymmetry that happens in the dual encoders model by introducing the cross-modal skip-connected network. Thus, we will mainly implement mPLUG model as well as OFA, which also ranked the second highest in COCO Image Captioning tasks, to fine-tune and test the dataset generated by the Text2Image tool.

Models	Data	COCO Caption							
		Cross-entropy Optimization				CIDEr Optimization			
		B@4	M	C	S	B@4	M	C	S
Encoder-Decoder	CC12M	-	-	110.9	-	-	-	-	-
E2E-VLP [19]	4M	36.2	-	117.3	-	-	-	-	-
VinVL [9]	5.65M	38.5	30.4	130.8	23.4	41.0	31.1	140.9	25.2
OSCAR [4]	6.5M	-	-	-	-	41.7	30.6	140.0	24.5
SimVLM _{large} [7]	1.8B	40.3	33.4	142.6	24.7	-	-	-	-
LEMON _{large} [33]	200M	40.6	30.4	135.7	23.5	42.3	31.2	144.3	25.3
BLIP [34]	129M	40.4	-	136.7	-	-	-	-	-
OFA [35]	18M	-	-	-	-	43.5	31.9	149.6	26.1
mPLUG	14M	43.1	31.4	141.0	24.2	46.5	32.0	155.1	26.0

Figure 3: Evaluation Results on COCO Caption "Karpathy" test split from paper (Li et al., 2022)

3 Methods Approaches

3.1 Dataset Generation

We used two tools: chatGPT and Midjourney to generate the dataset. This dataset is the first AI-generated dataset in the field of image caption.

There are several commands that were sent to chatGPT to help us to generate the textual side of the dataset. The commands are as follows:

1. Generate some random descriptive texts that are like image captions.

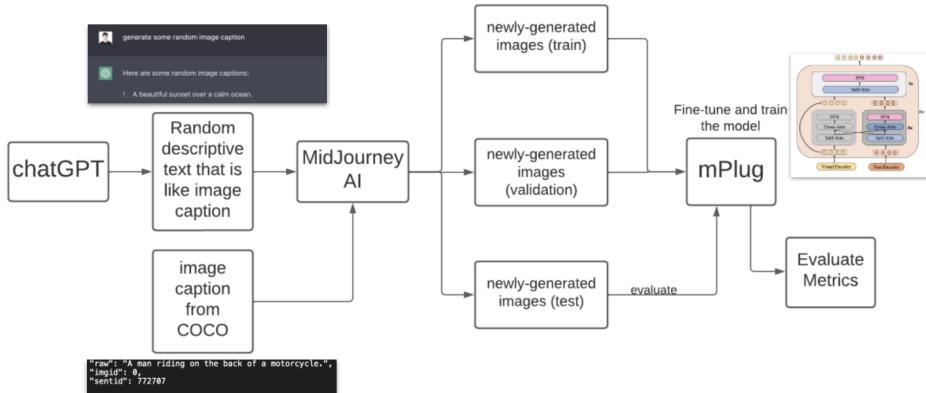


Figure 4: Our Method

- 233 2. For each sentence you input, give me five sentences with similar meanings, but with different structures.
- 234 3. For each sentence given below, extract the objects and combine the objects with "".
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238 And the following three images are sample tests on each command on chatGPT.

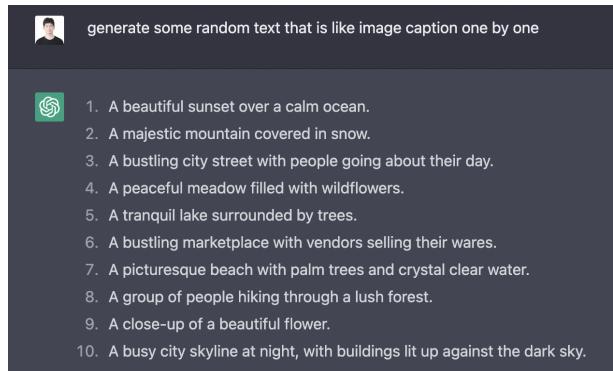


Figure 5: chatGPT sample result with command 1

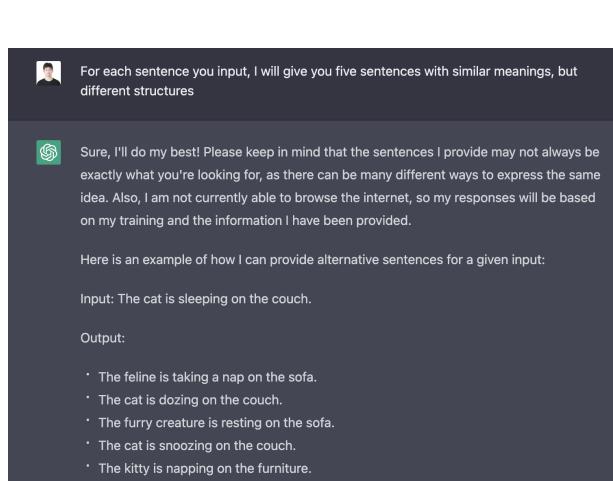


Figure 6: chatGPT sample result with command 2

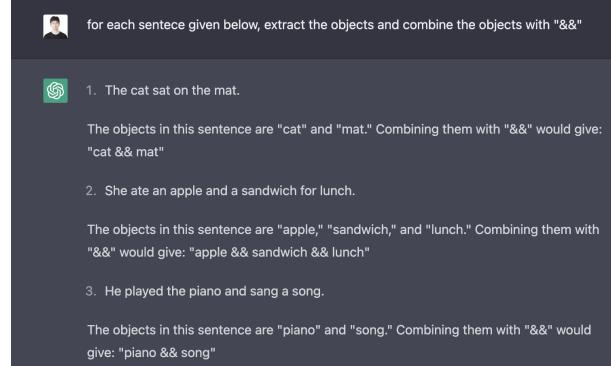


Figure 7: chatGPT sample result with command 3

We use Midjourney to generate the visual side of the dataset. The basic command is shown in Figure 8. We also used some advanced commands such as setting image size, upscaling, and making variations. An example of the image output is shown in Figure 1.

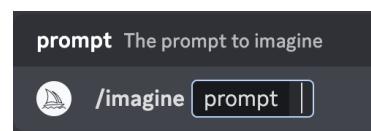


Figure 8: midjourney command

We generated two datasets based on the above method. In the first dataset, all image prompts were generated by chatGPT, and there are 45 images in total. And we split the dataset into training and testing partitions with 23 image-text pairs for the train and 22 image-text pairs for the test. In the second dataset, we mixed the image prompts generated by chatGPT with the captions given in the existing dataset COCO. The portion of them is 1 : 1. In this dataset, we generated 100 images using Midjourney in total. And we split the dataset into

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257 training and testing partitions with 80 image-text
258 pairs for the training and 20 image-text pairs for
259 the test. There are some sample train images with
260 captions given in the appendix.

261 For each prompt and image pair, there are five
262 image captions based on synonym conversion, and
263 one object label generated by chatGPT. The final
264 step is that we combined the image names, cap-
265 tions, and object labels together and transferred
266 them into a JSON file in the same structure as the
267 image caption JSON file for the COCO dataset us-
268 ing python. Note that the paring of the image and
269 its corresponding text is based on image generated
270 time since we generated each image based on the
271 prompts line by line.

272 3.2 Reproduce the Paper Result

273 To implement mPLUG model and OFA model on
274 our dataset, we first try to reproduce the paper’s
275 result with official open-source code.

276 For the mPLUG model, we used the pre-trained
277 model `mplug.en.base` from code (Li et al., 2022).
278 This model was pre-trained for 30 epochs with a
279 total batch size of 1024. The text encoder and the
280 skip-connected network are initialized with layers
281 from the *BERT_{base}* model, and the visual encoder
282 is initialized by CLIP-ViT. The base architecture
283 for the visual transformer is using the ViT-B/16
284 backbone. It uses an AdamW optimizer with 0.02
285 of weight decay as a preset, and with a learning
286 rate warmed-up to 1e-5.

287 To run the test on MS COCO data, we use the
288 Karpathy split the same as used in mPLUG paper,
289 and set the learning rate unchanged as 1e-5, batch
290 size equals to 64. After 5 epochs, the evaluation
291 results in BLEU-4, METEOR, CIDEr, and SPICE
292 all reach the baseline of mPLUG.

293 We also take a similar hyperparameter setting
294 to test of OFA model. In the reproduction of base-
295 line models on the MSCOCO image captioning
296 dataset, we use the *OFA_{Base}* model, which uses
297 ResNet101 as the backbone encoder, and has the
298 same Hidden layer size as the mPLUG model we
299 used. With a learning rate equal to 1e-5, and batch
300 size equal to 64, we can get similar or even better re-
301 sults on top of the baseline results of the *OFA_{Base}*
302 model(Table 2).

303 3.3 Fine-tune and Test on Midjourney Dataset

304 Our fine-tuning and testing is a two-stage process.
305 In both stages, we initialize our model with the
306 pre-trained weights of mPLUG.en.base. We first

307 experiment with a small Midjourney dataset with
308 only 45 images. In this stage, we finetune the im-
309 ages with the first 23 images and test the rest 22
310 images. We also apply random data augmentations
311 such as flipping, shearing, or rotating. This stage is
312 for verifying the basic functionalities of the model
313 and helping us understand the gap between the pre-
314 trained tasks and the specific downstream task on
315 our Midjourney dataset.

316 For the second stage, we generate more images
317 and divide the dataset with 100 images into 80 im-
318 ages for training and 20 images for testing. We
319 finetune and test the images with the same pro-
320 cess discussed above. Specifically, we finetune
321 the dataset with different epochs (5, 30, 50), learn-
322 ing rates (1e-6, 1e-5, 1e-4), and batch sizes (1, 8,
323 16, 32). For every configuration, we record the
324 highest result computed by the evaluation metrics
325 discussed in section 4. This stage generates the
326 final results used for analysis.

327 4 Evaluation and Analysis

328 For the purpose of image caption, a model must
329 produce a relevant and fluid caption for each im-
330 age. We analyze picture captioning on two datasets
331 COCO Caption and our own Midjourney dataset.
332 For the COCO Caption dataset, we are reproduc-
333 ing the results evaluated by the following metric
334 techniques discussed below. As for the Midjourney
335 dataset, we finetune the mPLUG by using the gener-
336 ated training dataset and then test the dataset using
337 the same metrics. We split the dataset into a ratio
338 of 4:1 for finetuning and testing the mPLUG on the
339 Midjourney dataset. In accordance with mPLUG,
340 we first adjust the model using cross-entropy loss
341 and then for an additional 5 epochs using CIDEr
342 optimization. (Li et al., 2022)

343 4.1 BLEU and BLEU-4

344 BLEU, or the Bilingual Evaluation Understudy, is
345 a score for comparing a candidate’s translation of
346 the text to one or more reference translations. The
347 BLEU metric ranges from 0 to 1. Few transla-
348 tions will attain a score of 1 unless they are identical to
349 a reference translation. Due to this, even a human
350 translator may not always receive a score of 1. For
351 BLEU, it is significant to note that the score in-
352 creases with the number of reference translations
353 present in each sentence. When we analyze the re-
354 sults from the COCO dataset and our own dataset,
355 we use the BLEU-4 metric that computes the cu-

Epoch	0	1	2	3	4	5
BLEU-4	39.6	43.11	45.21	46.83	46.99	47.45
METEOR	29.51	37.71	32.62	33.11	33.35	33.59
ROUGE_L	58.53	61.81	62.95	63.71	63.91	64.24
CIDEr	130.99	142.85	148.34	152.62	153.43	155.53
SPICE	22.99	24.39	25.02	25.57	25.61	25.85

Table 1: Reproduction Results of mPLUG.en.base Model (data shown in percentage form)

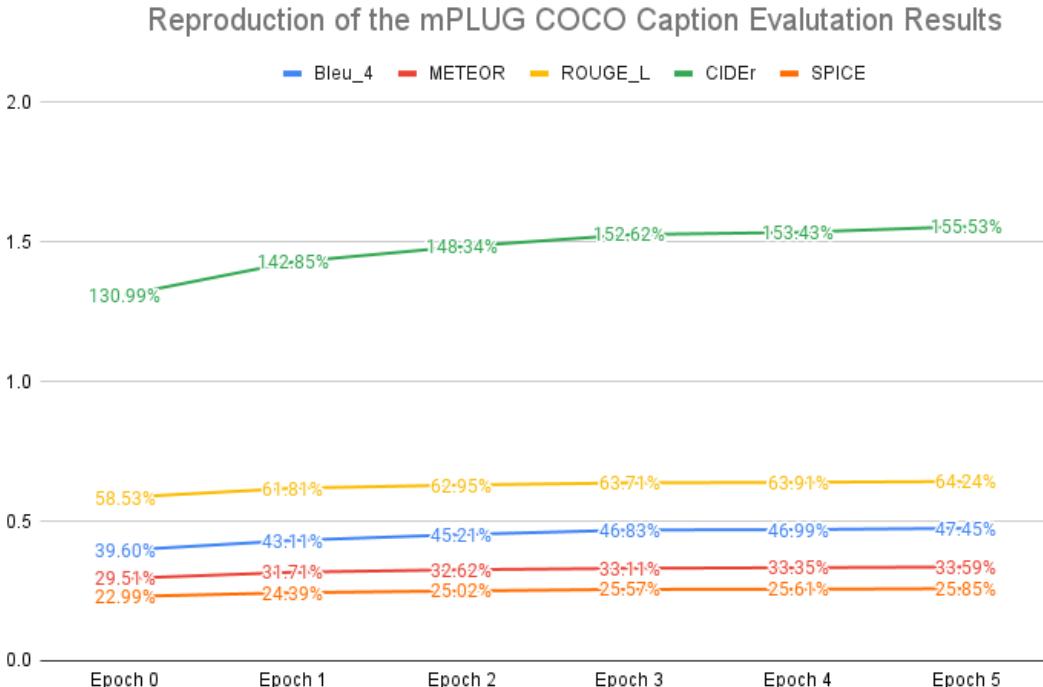


Figure 9: Reproduction Results in line chart form

mulative score which refers to the calculation of all individual 4-gram scores from 1 to 4, weighting them by computing the weighted geometric mean. (Papineni et al., 2002)

4.2 CIDEr

The CIDEr metric compares a generated sentence to a set of human-written ground truth sentences to determine how close they are. This metric has shown high agreement with consensus as assessed by humans. The concepts of grammaticality, saliency, relevance, and accuracy (precision and recall) are essentially captured by the CIDEr metric using sentence similarity. (Vedantam et al., 2014)

4.3 METEOR

The Meteor automatic evaluation metric scores machine translation hypotheses by aligning them to

one or more reference translations. The criteria used to align words and phrases are exact, stem, synonym, and paraphrase matches. The alignments between hypothesis-reference pairings are used to determine the segment and system-level metric scores. (Banerjee and Lavie, 2005)

4.4 ROGUE-L

ROUGE, or Recall-Oriented Understudy for Gisting Evaluation, is used to assess automatic summarization and machine translation software in natural language processing. The L stands for the longest common subsequence (LCS). One advantage of using LCS is that it does not require consecutive matches but in-sequence matches that reflect sentence-level word order as n-grams. The other advantage is that it automatically includes the longest in-sequence common n-grams, therefore no

	BLEU-4	METEOR	CIDEr	SPICE
<i>OFA_{Base}</i>	43.6	28.2	139.8	26.2
<i>OFA_{Base}</i> Baseline	42.8	31.7	146.7	25.8

Table 2: Reproduction Results of *OFA_{Base}* Model

389 predefined n-gram length is necessary. (Lin, 2004)

390 4.5 SPICE

391 The SPICE metric is a relatively new metric that
392 is used to analyze the ability that picture captions
393 can identify objects, properties, and relationships
394 between them. It has shown that SPICE reflects
395 human judgment over model-generated captions on
396 natural picture captioning datasets better than other
397 n-gram metrics as Bleu, METEOR, ROUGE-L, and
398 CIDEr. (Niu et al., 2022)

399 4.6 Choose between metrics

400 This downstream task mainly focuses on the ability
401 to describe the generated image. Thus, we focus
402 more on the precision of the generated sentence.
403 So when finetuning the dataset, we choose the best
404 configuration based on BLEU-4 and CIDEr score.

405 5 Discussion of Results

406 Let's denote the dataset that only has chatGPT
407 generated prompts and 45 images as "Old Dataset"
408 and the dataset which mixed prompts with captions
409 from the COCO dataset and 100 images as "New
410 Dataset".

411 For the image caption model, we use the pre-
412 trained model mPLUG base with Visual Backbone
413 VIT-B-16, Text Enc Layers 6, Fusion Layers 6,
414 and Text Dec Layers 6. The model was trained
415 using the Midjourney dataset corresponding to the
416 image-caption pairs, and it was applied to predict
417 image captions for the unseen images in the test set.
418 For each unseen image, we collected five image
419 captions generated by chartGPT based on its image
420 prompt.

421 We first tried different combinations of hyper-
422 parameters, such as learning rate, batch size, and
423 epoch on "Old Dataset". We experimented with
424 batch size equal to 64, learning rate(lr) equals to
425 1e-5 as default, and training 5 epochs, the best
426 result was in epoch 3, which has reached 133.39
427 percent on CIDEr score. Then we lower the batch
428 size to 8 and keep other hyperameters unchanged,
429 we got lower scores on all evaluation metrics. We
430 then altered the learning rate to 1e-4, the results

431 seem improved a little bit, but still underperform
432 than baseline tasks on Image Captioning.

433 For the Old Dataset, we found that no matter
434 how we change the hyper-parameters, the training
435 process tends to make the evaluation metrics worse.
436 For example, in the case of batch size 8 and learning
437 rate 1e-4, we trained for 50 epochs. But as
438 the epoch increases, almost all the evaluation
439 metrics decrease dramatically, where the CIDEr value
440 decreases from 121.07 to 73.25.

441 Therefore, we tried to create the "New Dataset"
442 from captions extracted from COCO and doubled
443 the size of our dataset. We then use similar hy-
444 perparameters (batch size = 64 and learning rate =
445 1e-5) to test the "New Dataset". From Figure 13,
446 we found that the best model finetuned to the New
447 Dataset was generally better than the best model
448 finetuned to the Old Dataset. For example, the
449 value of CIDEr increased from 133.4 to 135.1.

450 6 Conclusion

451 In conclusion, we proposed a method that uses
452 the Text2Image generator Midjourney AI to gener-
453 ate datasets for Image Captioning. We use Image
454 Captioning tools such as mPLUG and OFA to pre-
455 dict the captions corresponding to those generated
456 images. Our evaluation results with different eval-
457 uation metrics didn't provide as good results as the
458 test on the MS COCO dataset, which shows that
459 this method for dataset generation still needs to be
460 modified and improved. Therefore, we provided
461 some solutions and further improvements:

1. The descriptive captions generated by chatGPT
462 is too abstract to create a graph. It's better to use a
463 more simple and clear text as original captions.
2. Limitation of Image Captioning model. The
465 pre-trained dataset resources are limited and less
466 creative, and the word embeddings are also limited
467 for predicting more complex words.
3. Improvement on dataset size. The quantity of
469 images we are able to generate at these states is
470 within a hundred, which is far less than the common
472 dataset for Image Captioning. With wide-range and
473 various datasets, we might generate a better result
474 by using them for Image Captioning.

Prompt to Midjourney	Generated image	Predicted caption
"a young girl inhales with the intent of blowing out a candle."		"a little girl is looking at a cake with lit candles on it."
"a bathroom that has a broken wall in the shower."		"a bathroom is shown with a broken wall and a broken sink"
"an airport filled with planes sitting on tarmacs."		"a large group of airplanes parked on a snowy airfield."

Table 3: Some sample Image Caption test result on the New Dataset

Comparison of Different Fine-Tune Parameters

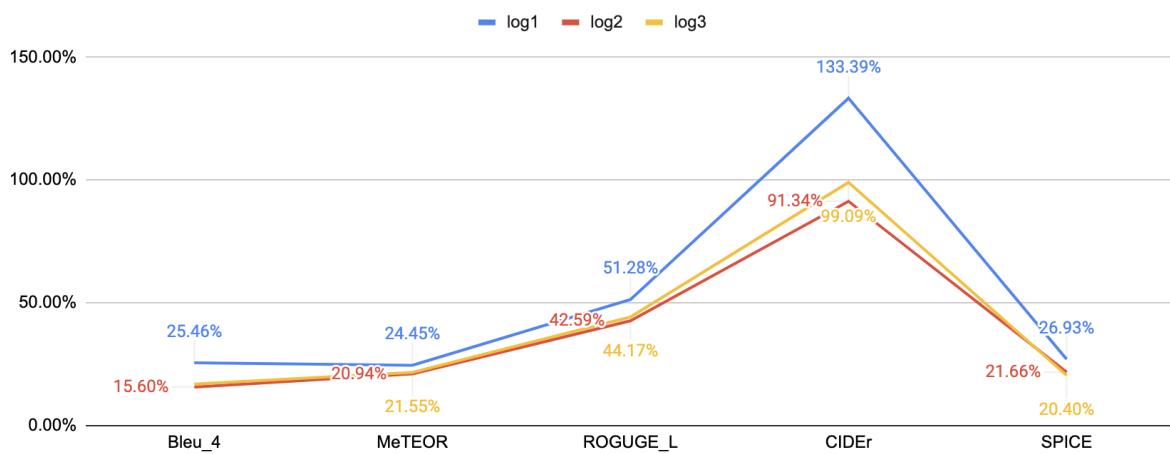


Figure 10: Fine-tune results picking from epoch with higher score. Log1: epoch 3, batch size = 64, lr=1e-5; Log2: epoch 5, batch size = 8, lr=1e-5; Log3: epoch 5, batch size = 8, lr=1e-4

Comparison of Old Dataset and New Dataset

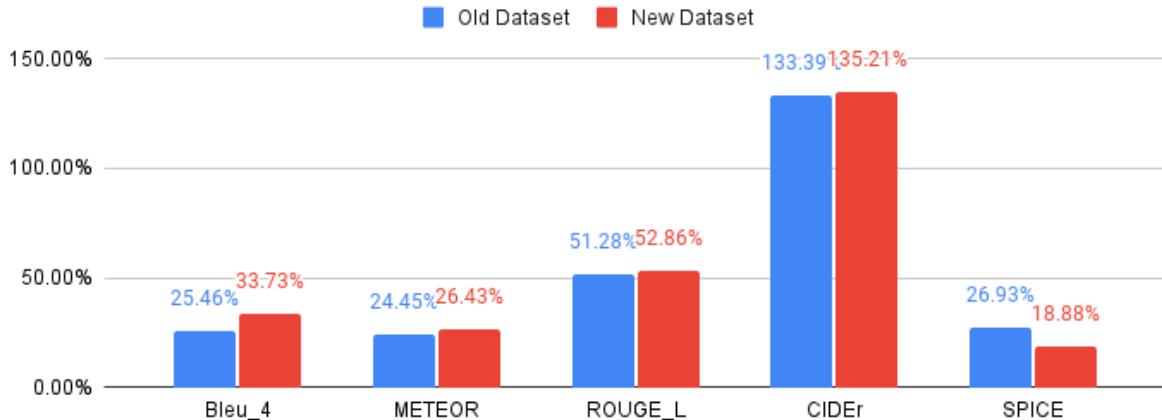


Figure 11: Comparison of Evaluation Results from Old Dataset and New Dataset

7 Division of Work

For the division of work, Ke Liu is responsible for finding previous work and reproducing the result using mPLUG and OFA model. Zhongqian Duan is responsible for generating the dataset. Lingjun Sun is responsible for the part of different evaluation metrics. We collaborated together to fine-tune the model and produce test results of our own dataset, and we also worked together to analyze our evaluation results as well as the problem of dataset generation.

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A Appendix

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Epoch	0	1	2	3	4
BLEU-4	20.61	24.55	24.74	25.46	24.77
METEOR	18.78	22.81	24.04	24.45	23.16
ROUGE_L	44.57	50.10	50.94	51.28	50.01
CIDEr	100.37	125.64	133.56	133.39	125.95
SPICE	19.73	25.84	26.07	26.93	26.36

Table 4: Evaluate result Log 1 with Dataset, batch size = 64, epoch = 5, default lr=1e-5

Epoch	0	5	10	15	20	30
BLEU-4	20.61	15.6	14.00	14.24	14.48	12.66
METEOR	18.78	20.94	20.30	20.54	20.18	19.53
ROUGE_L	44.57	42.59	40.29	41.04	42.13	40.81
CIDEr	100.37	91.34	84.25	89.13	85.59	82.52
SPICE	19.73	21.66	21.04	21.75	20.77	20.94

Table 5: Evaluate result Log 2 with Dataset, batch size = 8, epoch = 30

Epoch	0	5	10	20	30	50
BLEU-4	18.07	16.78	9.43	7.16	10.39	7.19
METEOR	22.16	21.55	19.64	19.07	20.46	19.72
ROUGE_L	46.59	44.17	41.83	38.37	38.47	38.37
CIDEr	121.07	99.09	83.62	72.41	77.16	73.25
SPICE	26.07	20.40	20.18	18.13	17.77	17.68

Table 6: Evaluate result Log 3 with Dataset, batch size = 8, epoch = 50, lr=1e-4

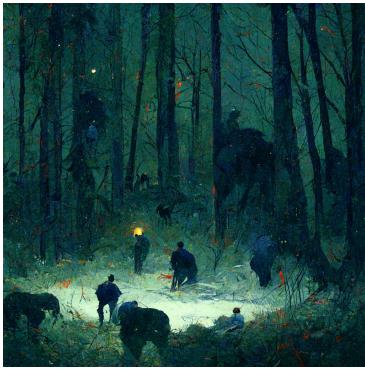
Prompt to Midjourney & Generated image	Image captions
A spaceship launching into the depths of space. 	<ul style="list-style-type: none"> • A spaceship is seen launching into space. • A spaceship is launching into the depths of outer space. • A spaceship is taking off and heading into space. • A spaceship is launching into the vast expanse of space. • A spaceship is being propelled into the depths of space.
People on bicycles ride down a busy street. 	<ul style="list-style-type: none"> • Cyclists are seen traveling on a busy street. • Bicycle riders are moving along a crowded street. • People on bikes can be spotted on a busy street. • Bicyclists are going down a busy street. • A busy street is filled with people on bicycles.
Animals hunting a man in the night in the large forest. 	<ul style="list-style-type: none"> • The animals were hunting the man in the night, stalking him through the large forest. • As the man ran through the dark forest, the animals pursued him, determined to catch their prey. • In the night, the animals hunted the man through the dense forest, their eyes shining in the darkness. • The man was the target of the animals' hunt as he ran through the forest, trying to escape their clutches. • The animals chased the man through the forest at night, their instinct to hunt driving them forward.

Table 7: Several example train images with their prompts and image captions