Learning Distinct and Representative Modes for Image Captioning

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Abstract

Over the years, state-of-the-art (SoTA) image captioning methods have achieved promising results on some evaluation metrics (*e.g.*, CIDEr). However, recent findings show that the captions generated by these methods tend to be biased to the "average" caption that only captures the most general mode (*a.k.a*, language patterns) in the training corpus, *i.e.*, the so called *mode collapse* problem. Affected by it, the generated captions are limited in diversity and usually less informative than natural image descriptions made by human. In this paper, we seek to avoid this problem by proposing a Discrete Mode Learning (DML) paradigm for image captioning. Our innovative idea is to explore the rich modes in the training caption corpus to learn a set of "mode embeddings", which allows the image captioning model to generate captions in various modes. Specifically, the proposed DML optimises a dual architecture that consists of an image-conditioned discrete variational autoencoder (CdVAE) branch and a mode-conditioned image captioning (MIC) branch. The CdVAE branch maps each image caption to one of the mode embeddings stored in a learned codebook, and is trained with a pure non-autoregressive reconstruction objective to make the modes distinct and representative. The MIC branch can be simply modified from an existing image captioning model, where the mode embedding is added to the original word embeddings as the control signal. In the experiments, we apply the proposed DML on two widely used image captioning models, Transformer and AoANet. The results show that the learned mode embedding successfully facilitates these models to generate high-quality image captions with different modes, further leading to a better performance for both diversity and quality on the MSCOCO dataset.

1 Introduction

Image captioning aims to generate natural descriptions for an given image. It is widely used in many real-world applications such as human-computer interaction, multi-modal recommendation, and hence has attracted lots of research attention. Recently, many state-of-the-art (SoTA) methods [19, 23, 52] have achieved promising results *w.r.t.* evaluation metrics like CIDEr [42], BLEU [34], and SPICE [1]. However, as discussed in [47], focusing on achieving higher scores on these metrics usually biases the image captioning models towards using only the common words, phrases and language patterns in the training corpus when describing the images (see Figure 1 for an example). In other words, the model automatically finds the most general sentence mode to perform captioning. As a result, the generated captions are limited in diversity both semantically and syntactically. This is far away from the ability of human beings as humans are able to describe the image in various ways.

The cause of this phenomena is widely known as the *mode collapse* problem and has been discussed in many generative models [16, 51]. Formally, given an input $\boldsymbol{x}$ and a generative model $\mathcal{G}$, mode

Submitted to 36th Conference on Neural Information Processing Systems (NeurIPS 2022). Do not distribute.

Captions generated by humans:
A man holding a white frisbee while standing on a field.
A man standing outside holding a frisbee in his hands.
A man is outside holding onto a frisbee disc.
A smiling man in the park with a frisbee.
A man is having a good time playing frisbee.

Captions generated by existing models:
Transformer: *A man holding a frisbee while standing in a field.*
AoANet: *A man holding a frisbee in a field.*

Captions generated by DML (Ours):
Mode-7: *There is a man playing with a frisbee.*
Mode-32: *Man in a blue shirt throwing a white frisbee.*
Mode-43: *A close up of a person with a frisbee.*
Mode-3: *A young man holding a white frisbee in his right hand.*
Mode-58: *A man is about to throw a frisbee.*

Figure 1: Captions written by humans vs. captions generated by existing models (Transformer [41] and AoANet [19]), and by our DML. The model-generated captions prefer to common words or phrases while captions derived from humans are more informative and diverse. The modes learned by our DML tend to yield certain and distinct language patterns in the generated captions, *e.g.*, mode-7 would like to generate caption with the pattern of *"There is ..."*, mode-3 is apt to use complex sentence while mode-58 is prone to a brief sentence.

collapse appears when the estimated output distribution $P_{\mathcal{G}}(\boldsymbol{x})$ assigns most of its probability mass to a small region of the output space, despite that the real output distribution $P_{\text{data}}(\boldsymbol{y})$ has a much larger variance. As a consequence, the randomly sampled outputs $\{\boldsymbol{y}_i \sim P_{\mathcal{G}}(\boldsymbol{x}) \mid i \in \mathbb{N}\}$ tend to be very similar. While mode collapse is typically a side effect for generative modelling, it is somewhat "welcomed" in SoTA image captioning models as it usually facilitates a higher evaluation performance. For example, CIDEr optimisation [37] based methods [11, 19] have significantly pushed the performance of image captioning to a new level on all mainstream evaluation metrics such as CIDEr, BLEU and SPICE. However, as shown in [28, 47], the success of CIDEr optimisation could be largely attributed to its ability of reducing the modes in the generated captions.

Some recent researches in image captioning have attempted to tackle the mode collapse problem so as to improve the diversity of the generated captions. Specifically, [3, 30, 45] adopt conditional variational autoencoders (CVAE) to encode the conditional distribution of the image captions into a low-dimensional continuous latent space $\mathcal{Z}$. When performing inference, these methods randomly sample latent variables from $\mathcal{Z}$ and input them into the caption decoder to drive it towards using different language patterns to describe the image. In this sense, the sampled latent variables can be considered as the continuous representations of modes interpolated from all occurred modes during training, thus alleviates the mode collapse phenomena to some extent. Nevertheless, it is still difficult to interpret the underlying conditional distribution, *i.e.*, which part of $\mathcal{Z}$ corresponds to which kind of language patterns in the real world. Thus, for the captions derived from two sampled mode representations, it is uncertain how they different from each other during the sampling process, as well as their qualities. To tackle this uncertainty, another line of works seeks to learn controllable image captioning models. For example, [9, 39] control the style of the image captions with learned sentiment or personality representations like "factual" or "humorous", "positive" or "negative", *etc*. [14] controls the syntactic structure of the image captions through part-of-speech tags. [10] focuses on different image regions to generate region-specific image captions. However, these methods rely on additional tools or annotations to supervise the learning of modes. More critically, this also restricts their modes within a pre-defined domain.

In this paper, we tackle the above problems by learning distinct and representative modes for image captioning through a new Discrete Mode Learning (DML) paradigm. Different with CVAE-based diverse image captioning methods, DML learns a codebook, which is an embedding matrix consisting of a set of mode embeddings that spans a discrete latent space, thus the language patterns encoded in different modes can be easily evaluated and are more perceptible. Different with previous controllable image captioning methods, DML requires no additional supervisions for mode and hence is not limited to the pre-defined set of control signals. Specifically, we optimise a dual architecture in the proposed DML: **Firstly**, an image-conditioned discrete variational autoencoder (CdVAE) branch,

where an encoder extracts the hidden states for all the reference captions paired with an image, and further quantise them using their matched mode embeddings in the codebook according to Euclidean distance. For the matching algorithm, we choose Hungarian algorithm instead of the naive nearest neighbour look-up, for which we find to be critical for increasing the number of effective modes. Afterwards, a decoder is used to reconstructs the reference captions in a *fully non-autoregressive* manner, which breaks the sequential dependencies on previous tokens and enforces the decoder to rely purely on the mode embeddings to generate different captions based on the same image feature, leading to more distinct and representative mode embeddings. **Secondly**, a mode-conditioned image captioning (MIC) branch, which can be simply modified from an existing image captioning model by adding the mode embedding to the original word embeddings as a control signal. During inference, the CdVAE branch is dropped, and the MIC branch is used to generate image captions with various language patterns according to the mode embeddings in the codebook.

In the experiments, we evaluate the effectiveness of our proposed DML paradigm by applying it to the widely-used Transformer [41] and the state-of-the-art AoANet [19], denoted by Transformer-DML and AoANet-DML, respectively. We observe that the learned modes in both models tend to yield clear language patterns in the generated captions, as shown in Figure 1, demonstrating that DML has successfully learned perceptible modes without explicit supervisions. We also find that our models perform surprisingly well under diversity evaluation (using metrics like SelfCIDEr [47]) and oracle performance evaluation (on all mainstream quality metrics like CIDEr [42]), achieving new state-of-the-art results. This shows that our learned modes are not only distinct, but also effectively cover the rich modes appeared within the dataset, which suggests that they are very representative. Moreover, we find that the models trained with DML outperform their original counterparts in terms of quality on some of the modes, meaning that DML can serve as a cost-free plugin for existing image captioning models.

In summary, the contributions of this paper are threefold:

- We propose a novel DML paradigm for image captioning. It is a dual architecture with a CdVAE branch that learns a codebook of mode embeddings, and a MIC branch which can be simply modified from an existing image captioning model to generates diverse captions based on the mode embeddings.
- To facilitate the learning of distinct and representative mode embeddings, we propose a mode assignment strategy based on Hungarian algorithm and a fully non-autoregressive objective for training the CdVAE branch.
- We conduct extensive experiments on two popular image captioning models to evaluate the effectiveness of the proposed DML, showing its superiority in terms of quality and diversity.

2 Related Works

Image captioning. Image captioning [2, 19, 44, 48] seeks to generate descriptions according to the given images, which has attracts much attention of the researchers. The conventional paradigm of image captioning models [15, 20, 44] mainly consists of two parts: a CNN-based image encoder and a RNN-based decoder for caption generation. Based on this diagram, many works [2, 19, 52] introduce the attention mechanism [41], which enforces models to consider more about the highlighted regions. Besides, to improve the performance, [49, 50] explore the visual relationships by constructing a semantic or scene graph, while [17, 37] optimise their models by Reinforcement Learning (RL) and directly use CIDEr [42] as the reward. However, these image captioning models mainly consider how to achieve higher evaluation scores, which usually bias the generated captions to an "average" version that contains the common words and phases in the training corpus only.

Diverse and controllable image captioning. Diverse image captioning aims at learning a model that can generate various captions based on the same image. To this end, CVAE-based models [6, 30, 45] learn a latent space during training and then generate diverse captions by sampling different priors from the latent space. GAN-based models [12, 22, 38] predict diverse captions by using different random noises as inputs accompanied with the given images. Although the diverse image captioning models are able to produce different captions during inference, it is still non-trivial to interpret the underlying conditional distribution, leading to an uncertainty of the model behaviour.

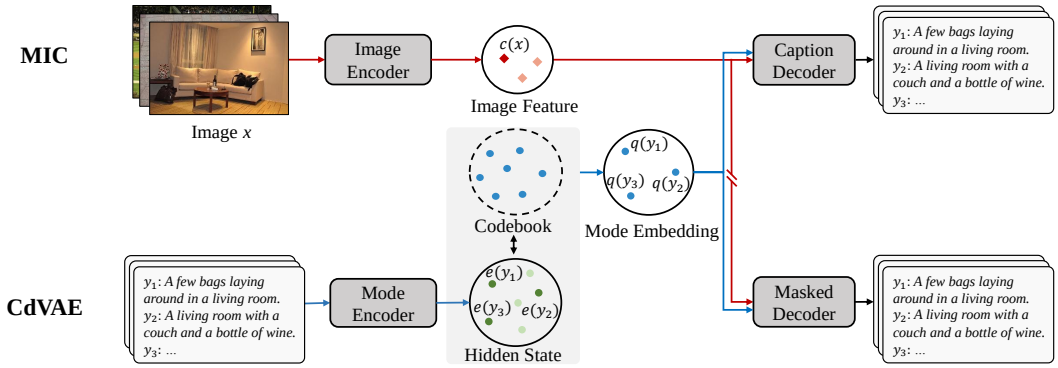


Figure 2: Overall of the Discrete Mode Learning (DML) paradigm that consisting of two branches: an image-conditioned discrete variational autoencoder (CdVAE) and a mode-conditioned image captioning (MIC). The "↔" denotes the matching operation by using Hungarian algorithm while the "\\" means there is no gradient flow.

To make the generated captions controllable, some works [7, 10, 13, 32, 33, 8] introduce an additional control signal. For example, Mathews *et al.* [32] provide a sentiment signal for each caption, and seek to control the sentiment of the generated captions. Similarly, Deng *et al.* [13] take the length of the caption as a control signal. Conditioned on different length embedding, the model is able to generate diverse descriptions based on the same image. Cornia *et al.* [10] seek to control the generated captions by using different visual objects in image as inputs. In this way, the models are able to choose a desired way to describe the given images, but they have to rely on the additional tools or annotations, which further limits the language pattern within a pre-defined domain.

3 Method

The overall architecture of the proposed Discrete Mode Learning (DML) paradigm is illustrated in Figure 2. It consists of two branches: an image-conditioned discrete variational autoencoder (CdVAE) branch, which contains a mode encoder $\mathcal{E}_m$ and a masked decoder $\mathcal{D}_m$; and a mode-conditioned image captioning (MIC) branch consists of an image encoder $\mathcal{E}_c$ and a caption decoder $\mathcal{D}_c$. The two branches are connected through a codebook Ω that contains a set of mode embeddings learned through the DML paradigm. During training, the model takes as input an image x and its paired reference captions $\{y_i\}_{i=1}^n$, and no additional supervisions are required. During inference, the CdVAE branch is dropped, and the MIC branch is used to generate image captions with various language patterns according to the mode embeddings in the codebook. See more details as follows.

3.1 Discrete Mode Learning

In a typical image captioning model, the training objective is to maximise $\log p(y_i|x)$ for each y_i in $\{y_i\}_{i=1}^n$, which is ill-posed since the model output is optimised to approach multiple different targets based on the same input, and usually leads to a mode collapse problem. Previous works alleviate this problem by introducing a latent variable z_i to the objective function, *i.e.*, $E_{z_i \sim p(z_i)}[\log p(y_i|x, z_i)]$, which serves as an explicit indication of mode and drives the model to generate different targets conditioning on different z_i. *E.g.*, in CVAE-based diverse image captioning models [45, 30], z_i is randomly sampled from a continuous latent space, which leads to an uncertainty of the model behaviour. While in some controllable image captioning models [14, 10], z_i needs to be pre-defined with the help of additional tools or annotations, which is usually restricted to a small set.

Unlike these methods, our DML samples latent variables from an embedding matrix $\Omega \in \mathbb{R}^{k \times d}$ which we call codebook. It defines a discrete latent space, where each entry in Ω corresponds to a potential mode embeddings, and k is a hyper-parameter representing the total number of modes in the codebook. During training, the mode encoder $\mathcal{E}_m$ is used to extract the representation for each caption y_i, denoted by $e(y_i)$, and match the representation with one of the entries in Ω. The matched

entry is then adopted as the mode embedding of y_i, denoted by $q(y_i)$, and the objective becomes:

$$\max_{\mathcal{E}_m, \mathcal{D}_m, \Omega} \log p(y_i|q(y_i), x), \quad \text{where } q(y_i) = \texttt{Match}(e(y_i), \Omega). \tag{1}$$

Here, $p(y_i|q(y_i), x)$ is the conditional distribution of the caption y_i given its mode embedding $q(y_i)$ and the paired image x, which is approximated with the masked decoder $\mathcal{D}_m$. $\texttt{Match}(\cdot, \cdot)$ indicates the matching operation. Note that, there is usually no real gradient defined for typical matching operators like the nearest neighbour look-up. Therefore, we follow [40] to first use the straight-through estimator to directly copy the gradients from $q(y_i)$ to $e(y_i)$, and then apply Vector Quantisation algorithm to move $q(y_i)$ towards $e(y_i)$ through mean square loss so as to train the matched codebook entries. The new training objective is

$$\mathcal{L} = -\log p(y_i|q(y_i), x) + \|\text{sg}[e(y_i)] - q(y_i)\|_2^2 + \beta \|e(y_i) - \text{sg}[q(y_i)]\|_2^2, \tag{2}$$

where the first term inherited from Eqn. (1) is used to optimise $\mathcal{E}_m$ and $\mathcal{D}_m$. The second term is used to train the matched entries in Ω. The last term is a commitment loss that is responsible for bounding the embedding space of Ω. $\text{sg}[\cdot]$ refers to "stop gradient" and β is a hyper-parameter.

3.2 Mode Encoding and Assignment in DML

We adopt a stack of N_e transformer encoder layers as our mode encoder $\mathcal{E}_m$. The input of $\mathcal{E}_m$ is y_i appended with a special `[MODE]` token to the start. The output of $\mathcal{E}_m$, $e(y_i) \in \mathbb{R}^d$, is the hidden state of the `[MODE]` token. When performing the matching process in Eqn. (1), an naive approach is to use the nearest neighbour look-up algorithm, *i.e.*,

$$q(y_i) = \Omega_\iota, \quad \text{where } \iota = \arg\min_j \|e(y_i) - \Omega_j\|_2. \tag{3}$$

However, we find in the experiments that in the models trained with this assignment strategy, the output of $\mathcal{E}_m$ quickly converges to the nearby of two or three mode embeddings in Ω, which is a clear sign of mode collapse (see Figure 5).

To avoid this, inspired by the object query assignment in [5], we treat the mode assignment of the captions as a Bipartite Graph Matching problem and solve it using Hungarian algorithm. Specifically, for all the reference captions $\{y_i\}_{i=1}^n$ paired with an image, we construct a bipartite graph between the output hidden states $\{e(y_i)\}_{i=1}^n$ from $\mathcal{E}_m$ and the mode embeddings in Ω. We first pad $\{e_i\}_{i=1}^n$ to the size of the codebook, k, with $\varnothing$ (assume $n < k$). Then, we search for a permutation of k elements τ with the lowest assignment cost:

$$\hat{\tau} = \arg\min_\tau \sum_i^k \|e(y_i) - \Omega_{\tau(i)}\|_2, \tag{4}$$

and the assigned mode embedding for each y_i is $q(y_i) = \Omega_{\hat{\tau}(i)}$. We find this assignment strategy greatly increases the number of effective mode embeddings in Ω (see Figure 5).

3.3 Fully Non-autoregressive Decoder

After getting the mode embeddings $q(y_i)$ for each caption y_i, we feed it together with the image features from x into a decoder to reconstruct y_i and estimate the conditional distribution $p(y_i|q(y_i), x)$ in Eqn. (2). In general, sequence generation models is often trained through the autoregressive Teacher Forcing scheme, which aims to maximise the likelihood of the ground-truth token w_t given all preceding ground-truth tokens $w_{j<t}$. In our setting, the objective function would be:

$$-\log p(y_i|q(y_i), x) = \sum_{t=1}^T -\log p(w_t|w_{j<t}, q(y_i), x) \tag{5}$$

where w_t is the t-th token in y_i and T is the total number of tokens in y_i. However, being able to access to the previous tokens causes the decoder to ignore the mode embedding when reconstructing y_i, since the previous tokens already provide enough information for the mode of y_i. As a result, the train signals for the mode embeddings could be useless.

Therefore, we propose to use a fully non-autoregressive (NAT) objective for the CdVAE branch of DML to facilitate the training of the mode embeddings. Specifically, the masked decoder $\mathcal{D}_m$ is a

stack of N_d transformer decoder layer that takes $q(y_i)$, x, and a sequence of T `[MASK]` tokens as input, and each target token is predicted in a conditionally-independent manner, *i.e.*,

$$-\log p(y_i|q(y_i), x) = \sum_{t=1}^{T} -\log p(w_t|\texttt{[MASK]}, q(y_i), x). \tag{6}$$

Apply this equation to Eqn. (2) will result in our final objective function for the CdVAE branch. We find this leads to more distinct and representative mode embeddings (see Figure 5).

3.4 Learning MIC Models with DML

So far we have introduced how DML learns the mode embeddings with the CdVAE branch. Here we show how to attach the CdVAE branch with an existing image captioning model to make it be aware of the mode of the generated captions. Specifically, in a standard encoder-decoder based image captioning model, the encoder $\mathcal{E}_c$ encodes the information from the image x into a sequence of hidden states, then the decoder $\mathcal{D}_c$ attends to the encoder hidden states and predict the ground-truth tokens in the reference caption y_i following the Teach Forcing scheme similar to Eqn. (5).

To adapt it into our DML framework, we only need to make a minor modification to the token embedding layer of $\mathcal{D}_c$ by adding the mode embedding $q(y_i)$ to the word embeddings of each token in y_i, resulting in our MIC branch. The training of MIC and CdVAE are performed jointly, using the objective functions in Eqn. (2) and Eqn. (5), respectively. In practice, we find the CdVAE branch is much harder to train than the MIC branch, due to its non-autoregressive prediction manner. To make the convergence speed of the two branch compatible, we let them use different batch sizes, *i.e.*, for each image, the CdVAE branch takes as input all its paired captions $\{y_i\}_{i=1}^n$, while the MIC branch randomly samples just one caption from $\{y_i\}_{i=1}^n$. Moreover, the gradient from the CdVAE branch will not be back-propagated to the image encoder.

Inference. During inference, the CdVAE branch is dropped, and the inference of MIC follows a very similar procedure as the original image captioning model. The only difference is that it requires selecting a mode embedding from the codebook and adding it to the input token embeddings.

4 Experiment

4.1 Dataset and Evaluation Metrics

Dataset. We train and evaluate our method on MSCOCO dataset [25] that contains $123,287$ images and each image is corresponding to at least 5 captions. In practice, we follow the settings in [31] that splits the data into $118,287$, $4,000$ and $1,000$ for training, validation and testing, respectively.

Quality evaluation. To assess the quality of the generated captions, we use five widely used evaluation metrics, *i.e.*, BLEU [34], ROUGE [24], METEOR [4], CIDEr [42], and SPICE [1]. Moreover, to further evaluate the performance of the generated captions, we employ another CLIP-based [35] metric namely ClipScore [18], which can assess whether the generated captions are semantically aligned with given images, even when they are totally different from the ground-truth/reference ones.

Diversity evaluation. To investigate the diversity of the generated captions, we use SelfCIDEr [46], mBLEU, and n-gram diversity (*i.e.*, Div-n [3]). All of these two metrics evaluate the diversity by comparing the differences among generated captions that belong to the same image.

4.2 Implementation Details

In the CdVAE branch, the number of transformer layers for $\mathcal{E}_m$ and $\mathcal{D}_m$ is set to 6 and 2, respectively. We use 12 attention heads and a hidden size of 768 for all transformer layers. β in Eqn. (2) is set to 0.25, following [40]. The number of mode embeddings in Ω is set to 64 by default. We convert each image to 100 object proposals by Faster RCNN [36] pre-trained on Visual Genome [21]. For the MIC branch, we take two widely used image captioning models, *i.e.*, Transformer [41] and AoANet [19], denoted by Transformer-DML and AoANet-DML separately. We train the models for 100,000 iterations with a batch of 64 images with all paired captions. We use AdamW [26] optimiser with a learning rate of 2e-4, and cosine decay it to 0. We train Transformer-DML and AoANet-DML on one NVIDIA 3090 GPU with about 10 and 13 GPU hours, respectively.

Table 1: Diversity evaluation on the best-5 sentences obtained from consensus re-ranking.

Methods	LNFMM [29]	COS-CVAE [30]	Seq-CVAE [3]	Transformer-BS	Transformer-DML
Div-1 (↑)	0.37	0.39	0.33	0.21	**0.43**
Div-2 (↑)	0.50	0.57	0.48	0.29	**0.59**
SelfCIDEr (↑)	-	-	-	0.57	**0.83**
mBLEU (↓)	0.64	**0.53**	0.64	0.78	0.54

Image			
Mode 7	*There is a man in the middle of a field playing with a frisbee*	*There is a man riding a motorcycle down the street*	*There is a man on a skateboard holding a can*
Mode 32	*Man in red shirt throwing a white frisbee*	*Man on a yellow motorcycle driving down the road*	*Man on skateboard with a beer on the ground*
Mode 43	*A close up of a person with a frisbee*	*A close up of a person riding a motorcycle on a road*	*A close up of a person on a skate board*
Mode 3	*A young man holding a white frisbee on top of a green field*	*A man riding a yellow motorcycle with a yellow helmet on*	*A young man holding a bottle of water while standing on a skateboard*
Mode 58	*A man getting ready to throw a frisbee*	*A man that is sitting on a motorcycle*	*A person on a court with a skateboard*

Figure 3: Samples of captions that generated based on different modes. Mode-7, mode-32 and mode-43 tend to generate the captions with a certain pattern, *i.e.*, *"There is ..."*, *"Man ..."*, and *"A close up of ..."*. Mode-3 is apt to use long sentences while mode-58 is prone to brief sentences.

4.3 Evaluation on Diversity

Quantitative results. In this part, we perform a diversity analysis for the proposed DML paradigm based on Transformer-DML. We compare our model with previous SoTA methods as well as Beam Search (BS) and show the results in Table 1. From the table, our DML-based model achieve higher performance on most of the diversity evaluation metrics, which demonstrates its effectiveness in learning distinct modes.

Qualitative results. We further provide several samples of the generated captions of our Transformer-DML model in Figure 3. We find that the learned modes exhibit clear and distinct language patterns. More specifically, mode-7, mode-32 and mode-43 tend to follow the patterns *"There is ..."*, *"Man ..."*, and *"A close up of ..."*, respectively. Mode-3 and mode-58 focus more on the semantic complexity of the caption, *i.e.*, mode-58 is likely to generate a brief caption while mode-3 is prone to the complicated one. These results show that for the same image, the mode embeddings learned through DML facilitate the model to generate captions in a various and comprehensible way. We show more qualitative results in the supplementary.

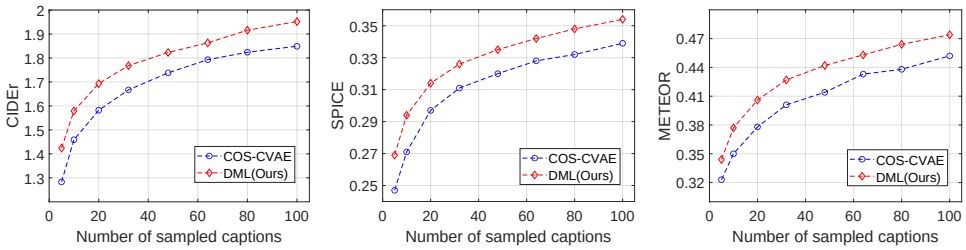
4.4 Evaluation on Quality

Oracle results. To investigate whether the embeddings in codebook are able to cover the rich modes appeared within dataset, we calculate the caption evaluation metrics in the oracle setting consistent with prior works [3, 29, 30], *i.e.*, taking the maximum score for each quality metric over all the candidate captions for each image. Specifically, we train Transformer-DML and AoANet-DML with codebook sizes $k = 20$ and $k = 100$, and evaluate the oracle results of the captions generated by all modes. In Table 2, the models with DML obtain the best and second best results on all the evaluation metrics *w.r.t.* both 20 and 100 samples. Moreover, we compare our DML paradigm with the SoTA baseline COS-CVAE by calculating the oracle scores of CIDEr, SPICE and METEOR with different numbers of samples. In Figure 4, the proposed DML consistently outperforms COS-CVAE on all settings. The high gain in quality metrics demonstrates that the proposed DML successfully captures the rich and representative modes in the training corpus.

Results of individual mode embedding. To assess the quality of captions generated using different modes, we calculate the evaluation scores of captions generated from some representative modes that are manually selected with distinct patterns. In Table 3, on mode-58, Transformer-DML outperforms the original Transformer on all reference-based metrics. Moreover, the Transformer-DML with

Table 2: Comparison with baselines *w.r.t.* oracle performance (*i.e.*, best-1 quality) on COCO dataset. "#Sample" refers to the number of generated captions for each image. The best and the second best results are highlighted with **bold** and underline, respectively.

Method	#Sample	B@1	B@2	B@3	B@4	R	M	C	S
Div-BS [43]	20	0.837	0.687	0.538	0.383	0.653	0.357	1.405	0.269
POS [14]		0.874	0.737	0.593	0.449	0.678	0.365	1.468	0.277
AG-CVAE [45]		0.834	0.698	0.573	0.471	0.638	0.309	1.259	0.244
Seq-CVAE [3]		0.870	0.727	0.591	0.445	0.671	0.356	1.448	0.279
COS-CVAE [30]		0.903	0.771	0.640	0.500	0.706	0.387	1.624	0.295
AoANet-DML (Ours)		**0.917**	**0.799**	**0.682**	**0.554**	**0.734**	**0.418**	**1.734**	**0.328**
Transformer-DML (Ours)		0.915	0.788	0.663	0.526	0.726	0.417	1.704	0.325
Div-BS [43]	100	0.846	0.698	0.555	0.402	0.666	0.372	1.448	0.290
POS [14]		0.909	0.787	0.672	0.550	0.725	0.409	1.661	0.311
AG-CVAE [45]		0.883	0.767	0.654	0.557	0.690	0.345	1.517	0.277
Seq-CVAE [3]		0.922	0.803	0.691	0.575	0.733	0.410	1.695	0.320
LNFMM [29]		0.920	0.802	0.695	0.597	0.729	0.402	1.705	0.316
COS-CVAE [30]		0.942	0.842	0.739	0.633	0.770	0.450	1.893	0.339
AoANet-DML (Ours)		**0.947**	**0.850**	**0.752**	**0.652**	**0.782**	**0.479**	**1.960**	**0.356**
Transformer-DML (Ours)		0.946	0.849	0.750	0.649	0.780	0.474	1.953	0.354



(a) CIDEr (b) SPICE (c) METEOR

Figure 4: Comparison between our DML and SoTA baseline COS-CVAE. We show the oracle results of CIDEr, SPICE and METEOR with different numbers of samples.

different mode embeddings can achieve better or at least competitive performance compared with the original Transformer in terms of ClipScore. We further report the best performed modes *w.r.t.* CIDEr, SPICE and ClipScore for AoANet-DML. In Table 3, the results show that the proposed DML can gain higher scores of CIDEr, SPICE and ClipScore by choosing the suitable mode embedding. These results suggest that our DML not only generates diverse results, but the results of each individual mode also yield a high quality.

4.5 Performance Analysis of the CdVAE branch

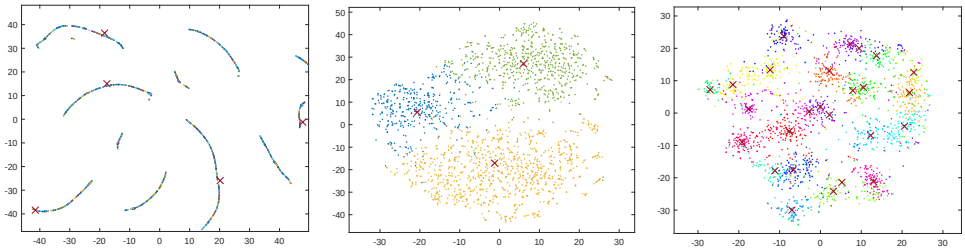
In this part, we investigate the effect of our mode assignment strategy (Section 3.2) and the fully non-autoregressive (NAT) objective (Section 3.3) of used by the CdVAE branch of DML. Specifically, we train Transformer models with a codebook size of $k = 64$ on three different settings: 1) DML w/o NAT objective; 2) DML w/o Hungarian assignment; 3) the proposed DML, and visualise their mode embeddings in the codebook and caption embeddings from the mode encoder output using t-SNE. We also present more analysis in the supplementary.

As shown in Figure 5(a), DML w/o NAT only activates 5 of 64 mode embeddings, *i.e.*, all caption embeddings are assigned to the 5 modes. Moreover, the caption embeddings of different modes are mixed together (zoom in to see the details) and are distributed among the twisted spaces nearby the mode embeddings, means that the mode embeddings and the caption embeddings may not contain useful information. The low oracle CIDEr score (1.207) also verifies this hypothesis.

In Figure 5(b), we show that DML w/o Hungarian assignment activates even fewer modes (*i.e.*, only three), and the caption embeddings have a more distinct distribution. This shows the importance of the fully NAT objective in CdVAE. Still, due to the small number of mode, the oracle CIDEr score in this setting is only 1.211, indicating a limited diversity.

Table 3: The performance of image captions generated by different modes. For Transformer-DML, we select some representative modes that exhibit clear language patterns or semantic complexities as shown in Figure 3. For AoANet-DML, we show the best performed modes in terms of CIDEr, SPICE and ClipScore, respectively (highlighted with underline). The original results of Transformer and AoANet are obtained using the code and settings in [27]. The best results of the two captioning methods on each metric are highlighted with **bold**.

Models	Mode	B@1	B@2	B@3	B@4	R	M	C	S	ClipScore
Transformer [41]	N/A	0.751	0.589	**0.448**	0.338	0.558	0.276	1.119	0.207	0.990
Transformer-DML	3	0.671	0.474	0.328	0.221	0.487	0.245	0.871	0.192	1.090
	7	0.677	0.497	0.359	0.253	0.499	0.247	0.958	0.189	0.967
	32	0.665	0.461	0.315	0.213	0.441	0.230	0.840	0.190	**1.121**
	43	0.658	0.481	0.339	0.238	0.479	0.234	0.909	0.175	1.098
	58	**0.752**	**0.590**	**0.448**	**0.340**	**0.559**	**0.277**	**1.124**	**0.208**	0.945
AoANet [19]	N/A	**0.770**	**0.613**	**0.476**	**0.368**	**0.571**	0.283	**1.173**	0.213	0.969
AoANet-DML	49	0.762	0.601	0.458	0.356	0.567	0.279	1.157	0.209	0.972
	64	0.658	0.461	0.315	0.212	0.529	**0.284**	0.768	**0.215**	1.131
	44	0.747	0.583	0.440	0.339	0.557	0.279	1.123	0.210	**1.195**



(a) DML w/o NAT objective (b) DML w/o Hungarian assign (c) DML

Figure 5: Effects of the Hungarian mode assignment and the fully non-autoregressive decoding objective. We visualise the mode embeddings (red "×") and the caption embeddings ("·" with other colours) on the test set by t-SNE. The inactivated modes are not shown for clearance.

Lastly, in Figure 5(c), our DML obtains 26 mode embeddings and the caption embeddings are tightly distributed around their corresponding mode embeddings. With 64 modes, our model achieves a oracle CIDEr of 1.871. These results demonstrate the effectiveness of the Hungarian mode assignment and the fully non-autoregressive objective for learning distinct and representative mode embeddings.

4.6 Limitation and Broader Impact

Limitation. Although our method can generate diverse captions based on different mode embeddings in the codebook, the more specific meaning of each mode is still unclear.

Potential negative societal impacts. The technology has a risk to be used maliciously to mimic the linguistic style of others, which may be misused to financial scams.

5 Conclusion

In this paper, we study a problem in image captioning that models tend to be biased to generate "average" caption, which contains the common words or phases only. To tackle this problem, we propose a Discrete Mode Learning (DML) paradigm for image captioning. The idea is to explore multiple rich modes in the training caption corpus to learn a codebook that contains a set of "mode embeddings", which enables the image captioning models to generate different captions based on various modes. Moreover, the proposed DML paradigm can be easily plugged into the existing image captioning models (*e.g.*, Transformer and AoANet) to generate high-quality and diverse captions.

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Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes] Please see the abstract and introduction in Section 1.
   (b) Did you describe the limitations of your work? [Yes] Please see the limitation in Section 4.6.
   (c) Did you discuss any potential negative societal impacts of your work? [Yes] Please see the potential negative societal impacts in Section 4.6.
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   (a) Did you state the full set of assumptions of all theoretical results? [N/A]
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