Non-Autoregressive Video Captioning with Iterative Refinement

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Abstract

Existing state-of-the-art autoregressive video captioning methods (ARVC) generate captions sequentially, which leads to low inference efficiency. Moreover, the word-by-word generation process does not fit human intuition of comprehending video contents (i.e., first capturing the salient visual information and then generating well-organized descriptions), resulting in unsatisfied caption diversity. In order to press close to the human manner of comprehending video contents and writing captions, this paper proposes a non-autoregressive video captioning (NAVC) model with iterative refinement. We then further propose to exploit external auxiliary scoring information to assist the iterative refinement process, which can help the model focus on the inappropriate words more accurately. Experimental results on two mainstream benchmarks, i.e., MSVD and MSR-VTT, show that our proposed method generates more felicitous and diverse captions with a generally faster decoding speed, at the cost of up to 5\% caption quality compared with the autoregressive counterpart. In particular, the proposal of using auxiliary scoring information not only improves non-autoregressive performance by a large margin, but is also beneficial for the caption diversity.

1. Introduction

Video captioning aims at automatically describing video contents with complete and natural sentences, where most recent works \cite{4, 25, 6, 27} adopt the encoder-decoder framework \cite{34} and achieve promising performance. In general, deep Convolutional Neural Networks (CNNs) are usually used to encode a video, whereas for decoding, Recurrent Neural Networks (RNNs) like LSTM \cite{21} or GRU \cite{8}, CNNs \cite{11, 14} and self-attention based transformer \cite{31, 35} have been adopted to generate captions. However, these decoders generate captions in a sequential manner, i.e., they condition each output word on previously generated outputs. Such autoregressive (AR) property results in low inference efficiency and is prone to error accumulation during inference \cite{3}. Moreover, AR decoders favor the frequent n-grams in training data \cite{10} and tend to generate repeated captions \cite{13}. Thus captions generated by AR methods are usually rigid and lacking in variability. While non-autoregressive (NA) decoding is proposed recently in neural machine translation (NMT) \cite{16} to generate sentences in parallel, the performance inevitably decline due to the poor approximation to the target distribution. Among the technical innovations to compensate the performance degradation, iterative refinement \cite{24, 14} can effectively bridge the performance gap between NA decoding and AR decoding.

Figure 1 illustrates the differences between AR decoding and iterative NA decoding. The word-by-word generation of AR decoding in Figure 1(a) may not fit the human intuition of comprehending video contents. In general, given a video clip, we are likely to be attracted by the salient visual information. Next, relying on the first-glance gist of the scene, we can produce a well-organized description by adjusting words order or replacing inappropriate words with proper ones. Thus, comprehending a video can be treated as a first visual then linguistic generation process. It can be observed that the iterative NA decoding in Figure 1(b) is more consistent with such process, whereas takes fewer
steps than AR decoding to generate a natural description.

To achieve the aforementioned first visual then linguistic generation, we first propose a non-autoregressive video captioning model (NAV) using a self-attention based decoder. For parallelization, the decoder is modified so that the prediction of each word can attend to the entire sequence. Besides, masked language modeling objective [12] is employed to train the proposed NAV. To enhance the robustness of NAV, we provide it with examples of different difficulties during training, i.e., target sequences are masked randomly according to a uniformly distributed masking ratio (ranging from zero to one). After training, NAV is capable of not only generating sentences from totally masked sequences but also predicting any proper subset of target words with rich bi-directional contexts.

To make full use of the capability of NAV, we propose an improved highly parallel decoding algorithm named mask-predict-interact (MPI) motivated by [14] to implement an iterative refinement procedure during inference. The original mask-predict algorithm [14] repeatedly masks out and re-predicts the subset of words that the NA model is least confident about. However, the confidence of NAV on words, as we will show, is not so credible. Therefore, we propose to additionally exploit external auxiliary scoring information to help the model accurately focus on inappropriate words during iterative refinement. To reduce the workload, we simply adopt ARVC that have the same architecture with our proposed NAV as an external teacher to provide complementary scoring information in this work. With such delicate designed iterative refinement procedure, a high-quality caption can be generated in a compositional manner, which can be treated as a first visual then linguistic generation process because salient visual information is more likely captured given few unmasked words in early iterations whereas grammatical errors are gradually removed in later iterations.

The main contributions of this work are three-fold. (1) To our knowledge, we are the first to sufficiently study non-autoregressive decoding in video captioning and systemically develop a non-autoregressive video captioning model (NAV) with iterative refinement. (2) We further propose to exploit external auxiliary scoring information to assist the NAV in precisely focusing on those inappropriate words during iterative refinement. (3) Extensive experiments show that with the aid of auxiliary information and iterative refinement, our proposed NAV generate more felicitous and diverse captions and decodes faster at a cost of as little as 5% caption quality compared with the autoregressive counterpart.

### 2. Background

In this section, we mainly talk about the differences between autoregressive (AR) decoding and non-autoregressive (NA) decoding.

#### 2.1. Autoregressive decoding

Given a clip of video $V$, the encoder aims to encode $K$ sampled frames/clips to the video representation $R = \{r_1, r_2, \ldots, r_K\}$, while the decoder attempts to decode $R$ to a sentence $S = \{s_1, s_2, \ldots, s_T\}$ with length $T$. In AR decoding, the generation process is triggered by the [BOS] (begin-of-sentence) token $s_0$ and terminated after generating [EOS] (end-of-sentence) token $s_T$. Formally, the model over parameters $\theta$ factors the distribution over possible output sentences $S$ into a chain of conditional probabilities with a left-to-right causal structure:

$$p_{AR}(S|R; \theta) = \prod_{t=1}^{T} p(s_t | s_{0:t-1}, R; \theta) \quad (1)$$

During training, the ground-truth sentences $S^*$ are usually used for supervision, which is known as teacher forcing technique [36]. Therefore, the model is trained to minimize the cross-entropy loss as follows:

$$\mathcal{L}_{AR}(\theta) = -\sum_{t=1}^{T} \log p_{AR}(S^* | R; \theta) \quad (2)$$

The mainstream AR decoders applied in video captioning include RNNs [27, 6, 34], CNNs [1, 4] and self-attention based transformer [31, 5]. Table 1 shows parallelization capability of different models in training and inference stages. It can be concluded that all AR models are not parallelizable during inference.

#### 2.2. Non-autoregressive decoding

To achieve parallelization in the inference stage, a solution is to remove the sequential dependency ($s_t$ depends on $s_{0:t-1}$). Assuming the target sequence length $T$ can be modeled with a separate conditional distribution $p_L$, then the NA decoding can be expressed as:

$$p_{NA}(S|R; \theta) = p_L(T|R; \theta) \prod_{t=1}^{T} p(s_t | R; \theta) \quad (3)$$

There are two main differences between NA decoding and AR decoding according to the Eq. (3) and Eq. (1).

| Models          | Training | Inference |
|-----------------|----------|-----------|
| AR models       | ×        | ×         |
| CNNs based      | ✓        | ×         |
| self-attention  | ✓        | ×         |
| NA models       | ✓        | ✓         |

Table 1. Parallelization capability of autoregressive (AR) models and non-autoregressive (NA) models in different stages.
Sequential dependency. After removing the sequential dependency, it makes a strong assumption in NA decoding that the individual token predictions are conditionally independent of each other. Although this modification allows for highly parallel decoding, another problem is inevitably introduced and leads to performance degradation. For example, a non-autoregressive translation model might consider two or more possible translations, A and B, it could predict one token from A while another token from B due to the complete conditional independence mentioned above. This problem is termed as “multimodality problem” [16] in non-autoregressive machine translation (NAT). To avoid conceptual confusion with “multimodality problem” and multimodal inputs in video captioning, we stick to use double quotation marks whenever this problem is mentioned. To compensate for the performance degradation brought by this problem, several technical innovations have been proposed in NAT including but not limited to:

- **Iterative refinement.** Ghazvininejad et al. [14] show that iterative refinement during inference can collapse the multi-modal distribution into a sharper uni-modal distribution, thus alleviating the “multimodality problem”.

- **Knowledge distillation.** Gu et al. [16] have discovered that training a NA model with distilled data generated by the AR counterpart performs better than the original ground-truth data. One possible explanation is that the distilled data is less noisy and more deterministic, eschewing the “multimodality problem”.

**Target sequence length.** In AR decoding, target sequence length \( T \) of a generated caption \( S \) can be dynamically determined by the [EOS] token. However, in NA decoding, \( T \) is modeled with a separate conditional distribution \( p_T \). Prior works in NAT determine \( T \) with following different methods: (1) using a fertility model [16], (2) applying a length classifier to predict the encoder’s outputs [24], (3) adding a special [LENGTH] token to the encoder for prediction [14], and (4) leveraging the statistics in training data [18] [35].

### 3. Non-Autoregressive Video Captioning

We begin this section by first presenting the architecture of our proposed non-autoregressive video captioning model (NAVC), followed by its training objective. Finally, inference rules of NAVC are discussed, where the mask-predict-interact decoding algorithm is introduced in details.

#### 3.1. Architecture

As shown in Figure 2, the architecture of our proposed NAVC consists of three parts, including a CNN-based encoder, a length predictor and a self-attention based decoder. Next, we will introduce them separately.

![Figure 2. The architecture of our proposed NAVC, which consists of a CNN-based encoder, a length predictor and a self-attention based decoder.](image)

#### 3.1.1 Encoder

In particular for a given video \( V \), we first sample it with \( K \) frames/clips \( V = \{v_1, v_2, \ldots, v_K\} \). Then the representation \( R \in \mathbb{R}^{T \times d_m} \) can be obtained by two subsequent transforms, which can be formalized as:

\[
R = T_{IEL}(T_{CNN}(V; \theta_1); \theta_2)
\]

(4)

where \( \theta_1, \theta_2 \) are trainable parameters within \( T_{CNN} \) and \( T_{IEL} \), respectively. Specifically, \( T_{CNN} \) represents a series of convolution and pooling operations in pre-trained 2D/3D CNNs, and it produces output of dimension \( d_1 \). Then \( T_{IEL} \) maps the input of dimension \( d_1 \) to the output of dimension \( d_m \) (model dimension of the decoder). Within \( T_{IEL} \), the shortcut connection in highway networks [28] is adopted.

So \( T_{IEL} \) can be defined as (omitting biases for clarity):

\[
T_{IEL}(x; \theta_2) = g \circ (1 - g) \circ \hat{x}
\]

\[
\hat{x} = \tanh(W_{e_2}x)
\]

\[
g = \sigma(W_{e_3}x)
\]

(5)

where \( \phi \) is the Hadamard (element-wise) product, \( W_{e_1} \in \mathbb{R}^{T \times d_1} \), \( \{W_{e_2}, W_{e_3}\} \in \mathbb{R}^{d_1 \times d_m} \) are learnable weights and \( \sigma \) is sigmoid activation function. In our preliminary experiments, adding the original encoder of transformer [31] right after the input embedding layer (IEL) does not promote the performance, so we just exclude it. In terms of integrating representations of multiple modalities \( (R_1, R_2, \ldots, R_{N_m}) \), the final video representation can be achieved by concatenating them along the temporal axis, i.e., \( R = \text{Concat}(R_1, R_2, \ldots, R_{N_m}) \).

#### 3.1.2 Length Predictor

Referring to Eq. (5), NAVC should know the sequence length \( T \) before decoding. So a length predictor (LP) over parameters \( \theta_3 \) is introduced to predict length distribution \( l \):

\[
l = LP(R; \theta_3) = \phi(W_{lp2}(\phi(W_{lp1}MP(R))))
\]

(6)
where \( l \in \mathbb{R}^{T_{\text{max}}} \) and \( T_{\text{max}} \) denotes the pre-defined maximum sequence length, MP denotes mean pooling (along the temporal axis), \( \phi \) is the ReLU activation function, \( W_{lp1} \in \mathbb{R}^{d_m \times d_m} \) and \( W_{lp2} \in \mathbb{R}^{T_{\text{max}} \times d_m} \) are learnable weights. As the ground-truth length distribution in training data is available, we formulate the length prediction as regression rather than classification. During training, we directly use the sequence length of ground-truth sentences. As for inference, we use the predicted \( l \) and further discuss it in Section 3.3.2.

### 3.1.3 Decoder

The decoder in NAVC has two kinds of capability, namely generating captions in parallel and predicting any subset of target words. To achieve the former capability, we adopt the original decoder of transformer [31] with only one modification, that is, removing the self-attention mask. By doing so, our decoder becomes bi-directional, thus the prediction of each token can use both left and right contexts.

3.2. Training Objective

Instead of training length predictor separately [24], we train end-to-end NAVC by jointly minimizing the length prediction loss \( \mathcal{L}_{\text{len}}(\hat{\theta}) \) and the captioning loss \( \mathcal{L}_{\text{cap}}(\bar{\theta}) \):

\[
\mathcal{L}_{\text{NAV}}(\theta) = \mathcal{L}_{\text{len}}(\hat{\theta}) + \mathcal{L}_{\text{cap}}(\bar{\theta})
\]

where \( \theta = \{\theta_{1:3}\} \) denotes all parameters in the NAVC, \( \hat{\theta} = \{\theta_{1:3}\} \) and \( \bar{\theta} = \theta \setminus \theta_3 \) denote the parameters that will be tuned under \( \mathcal{L}_{\text{len}} \) and \( \mathcal{L}_{\text{cap}} \), respectively. In particular, we fix the parameters in pre-trained CNN (i.e., \( \theta_1 \)) like most previous works [6, 27] did, although fine-tuning might bring performance improvement [25]. We adopt the smooth \( L_1 \) loss [15] for length prediction given the predicted distribution \( l \) and ground-truth distribution \( l^* \):

\[
\mathcal{L}_{\text{len}}(\hat{\theta}) = \sum_{j=1}^{T_{\text{max}}} \text{smooth}_{L_1}(l_j^* - l_j)
\]

\[
\text{smooth}_{L_1}(x) = \begin{cases} 
0.5x^2 & \text{if } |x| < 1 \\
|x| - 0.5 & \text{otherwise}
\end{cases}
\]

As for the captioning loss, we optimize the cross-entropy loss over every masked token \( s \in S_{\text{mask}} \):

\[
\mathcal{L}_{\text{cap}}(\bar{\theta}) = -\sum_{s \in S_{\text{mask}}} \log p(s|R, S_{\text{part}}; \bar{\theta})
\]

### 3.3. Inference Rules

In order to make full use of the capability of well-trained NAVC, we propose a decoding algorithm named mask-predict-interact (MPI) that enables the model to refine captions iteratively. Compared with the original mask-predict algorithm [14], our MPI additionally exploits external auxiliary scoring information because of the low reliability of NAVC’s confidence on generated tokens, which will be shown in Section 3.3.3. In order to reduce the workload, we simply utilize a well-trained ARVC, which has the same architecture as NAVC, and treat it as an external teacher.

During inference, the decoding starts with totally masked sequences. Then the proposed MPI is able to produce high-quality sentences within a few numbers of iterations. At each iteration, tokens with low confidence are masked and re-predicted, allowing the model to give a second thought to those uncertain tokens. Moreover, with the aid of auxiliary information provided by ARVC, the inappropriate tokens (e.g., words that make the sentence not smooth) are more likely to be focused on.

### 3.3.1 Formal Description

Here, we define six variables: the number of iterations \( I \), the input sequence \( X^{(i)} (i \in [0, I]) \), the output sequence \( Y^{(i)} \), the NAVC’s confidence \( U^{(i)} \) on \( Y^{(i)} \), the ARVC’s confidence \( Z^{(i)} \) on \( Y^{(i)} \), and the overall confidence \( C^{(i)} \) on \( Y^{(i)} \).

**MASK.** For the first iteration \( (i = 0) \), \( X^{(0)} \) is a totally masked sequence. While for later iterations \( (i \in [1, I]) \), we apply Select-and-Mask-Out (SaMO) operation, where \( n \) tokens of previous generated sequence \( Y^{(i-1)} \) will be masked based on the confidence \( C^{(i)} \), to yield \( X^{(i)} \):

\[
X^{(i)} = \begin{cases} 
\{m, m, \ldots, m\} & \text{if } i = 0 \\
\text{SaMO}(Y^{(i-1)}; C^{(i-1)}, n) & \text{otherwise}
\end{cases}
\]
where \( m \) is the [MASK] token. We adopt a deterministic SaMO operation like [13], i.e., we mask out top \( n \) tokens with the lowest confidence and keep the rest unchanged:

\[
x_t(i) = \begin{cases} 
m & \text{if } t \in \arg \min(c_t(i-1), n) \\
y_t(i-1) & \text{otherwise} 
\end{cases}
\]

We use linear decay masking ratio \( r = \max(\frac{T-t}{T}, \lambda) \) with lower bound \( \lambda \) to decide \( n \), thus \( n = T \cdot r \).

**Predict.** Next, we feed \( X(i) \) to the NAVC and collect its prediction results \( Y(i) \) and confidence \( U(i) \). Specifically, we adjust \( y_t(i) \) and \( u_t(i) \) if only if \( x_t(i) \) is a [MASK] token:

\[
y_t(i) = \begin{cases} 
    x_t(i) & \text{if } x_t(i) \neq m \\
    \arg \max_w p(s=w|X(i)) & \text{otherwise}
\end{cases}
\]

\[
u_t(i) = \begin{cases} 
    u_t(i-1) & \text{if } x_t(i) \neq m \\
    \max_w p(s=w|R,X(i)) & \text{otherwise}
\end{cases}
\]

Since NAVC is trained with masked language modeling objective [12], \( u_t(i) \) reveals the semantic consistency of \( y_t(i) \).

**Interact.** After masking and predicting, the teacher (ARVC) will give a mark to the generated sentence \( Y(i) \):

\[
z_t(i) = p(s=y_t(i)|y_{<t}, R)
\]

Since autoregressive decoders favor the frequent n-grams appeared in the training data [10], \( z_t(i) \) to some extent reveals the coherence between \( y_t(i) \) and previous generated words \( y_{<t} \). For the next SaMO operation (Eq. [12] [13]), if \( C(i) = U(i) \), it is exactly the mask-predict algorithm [14]. We, instead, jointly consider the confidence from both NAVC and auxiliary teacher (ARVC) on \( Y(i) \):

\[
C(i) = \sqrt{U(i) \cdot Z(i)}
\]

### 3.3.2 Deciding Target Sequence Length

Following the common practice of noisy parallel decoding [16] [35], we select top \( L \) length candidates with the highest values from \( i \) during inference, which is similar to the beam size in beam search, and decode the same example with different lengths in parallel. We then utilize the overall confidence \( C(I-1) \) at the last iteration and select the sequence with the highest average log-probability as our hypothesis:

\[
\frac{1}{T} \sum_{i=1}^{T} \log C(i-1)
\]

### 3.3.3 Example

Figure 5 illustrates how our proposed MPI can generate a good caption with the sequence length \( T = 6 \) in just three iterations \( (I = 3) \). And meanwhile, a comparison between MPI and MP within finite iterations is also detailed.

**How our MPI works.** At the first iteration \( (i = 0) \), the input sequence \( X(0) \) is a totally masked sequence. Then NAVC predicts \( Y(0) \) and \( U(0) \) in a purely non-autoregressive manner, producing a ungrammatical caption \( Y(0) \) with captured salient visual information (“a group of people”). Next, \( Y(0) \) is fed into ARVC (the auxiliary teacher) to achieve its scoring information \( Z(0) \), so that the overall confidence \( C(0) \) of \( Y(0) \) can be calculated.

At the second iteration \( (i = 1) \), we select 4 of the 6 tokens \( (n = 6 \times \frac{3}{4} = 4) \) of previously generated \( Y(0) \) with lowest confidence \( C(0) \), mask them out to obtain \( X(1) \) and re-predict them to generate \( Y(1) \). We observe that \( Y(1) \) describes video content correctly with no grammatical errors. Moreover, the token “are” \( y(1) \) have higher \( z(1) \) score than \( z(2) \), showing that ARVC believes “are” is more suitable than “a” for putting after “a group of people”.

At the last iteration \( (i = 2) \), we mask out 2 of the 6 tokens of \( Y(1) \) with lowest confidence \( C(1) \) to get \( X(2) \). Now
that 4 of the 6 tokens are available, NAVC is able to predict $Y^{(2)}$ more precisely. Although $Y^{(2)} = Y^{(1)}$ in this case, NAVC is more confident about “group” and “dancing”.

The differences between MPI and MP. In terms of formula, our MPI additionally influences masking decision (Eq. (17, 12)) and candidate decision (Eq. (18)). As for the qualitative example (the right part of Figure 3), the final sentence generated by MP is quite different from our expectations. Specifically, at the end of the first iteration, MP decides to mask out and re-predict the tokens “group”, “of”, “people” and “class”, which imperceptibly leads to a wrong direction. At later iterations, due to the decay of the masking ratio, the sentence becomes more deterministic. Therefore, the inappropriate token “is” ($y^{(2)}_3$) is hard to be adjusted again, especially with the immediately following token “in” rather than “people”. In short, iterative refinement might exhibit an inherent defect that unsuitable SaMO operations in early iterations might result in inelicitous captions. Compared with MP, MPI is more likely to focus on inappropriate words, relieving the inherent defect.

4. Experiments

4.1. Datasets and Implementation Details

We evaluate using two popular benchmark datasets from the existing literature in video captioning, namely Microsoft Video Description (MSVD) dataset [17], and MSR-Video To Text (MSR-VTT) dataset [37]. Three common metrics are adopted, including BLEU [26], METEOR [2] and CIDEr [32]. All metrics are computed using the API released by Microsoft COCO Evaluation Server [7]. More details can be found in supplementary materials.

4.2. Experiment Results

4.2.1 Autoregressive Results

We first compare our ARVC with recent state-of-the-art approaches to verify the effectiveness of the overall arch.

| Model                | Iteration (I) | MSVD       |           | MSR-VTT    |           |
|----------------------|---------------|------------|-----------|------------|-----------|
|                      |               | B@4 | M | C | Latency | SpeedUp | B@4 | M | C | Latency | SpeedUp |
| ARVC ($b = 1$)       | I             | 48.6 | 34.3 | 87.5 | 19.1 ms | 1.55× | 41.6 | 28.3 | 48.6 | 22.3 ms | 1.60× |
| ARVC ($b = 5$)       | I             | 49.7 | 34.9 | 91.8 | 29.6 ms | 1.00× | 42.4 | 29.1 | 50.8 | 35.6 ms | 1.00× |
| Base (NAVc$_{mp}$)   |               | 1    | 52.4 | 33.3 | 81.3 | 6.6 ms | 4.84× | 24.2 | 21.5 | 35.1 | 7.1 ms | 5.01× |
|                      |               | 2    | 53.1 | 33.5 | 80.6 | 11.4 ms | 2.60× | 36.0 | 25.4 | 42.2 | 12.7 ms | 2.80× |
|                      |               | 5    | 52.7 | 34.0 | 82.0 | 26.0 ms | 1.14× | 38.9 | 26.4 | 45.0 | 26.9 ms | 1.32× |
| Full (NAVc$_{mpi}$)  |               | 1    | 51.7 | 34.3 | 85.4 | 9.3 ms | 3.18× | 26.2 | 22.6 | 37.4 | 9.7 ms | 3.67× |
|                      |               | 2    | 52.8 | 35.5 | 89.4 | 16.4 ms | 1.80× | 39.6 | 27.0 | 46.3 | 16.8 ms | 2.12× |
|                      |               | 5    | 51.4 | 35.1 | 88.0 | 38.1 ms | 0.78× | 42.5 | 28.0 | 49.4 | 39.7 ms | 0.90× |

Table 2. Captioning performance comparison on both MSVD and MSR-VTT datasets, where B@4, M and C are short for BLEU@4, METEOR and CIDEr, respectively. $b$ means the beam size in beam search. Latency is computed as the time to decode a single sentence without minibatching, averaged over the whole test set. The decoding is implemented in PyTorch on a single NVIDIA Titan X.

| Dataset   | MSVD       | MSR-VTT    |
|-----------|------------|------------|
|           | B@4 | M | C | B@4 | M | C |
| RecNet (IR$_1$) [34] | 52.3 | 34.1 | 80.3 | 39.1 | 28.6 | 42.7 |
| E2E (IR$_2$) [25]   | 50.3 | 34.1 | 87.5 | 40.4 | 27.0 | 48.3 |
| MGSA (IR$_2$+C) [6] | 53.4 | 35.0 | 86.7 | 42.4 | 27.6 | 47.5 |
| MARN (R+RX) [27]    | 48.6 | 35.1 | 92.2 | 40.4 | 28.1 | 47.1 |
| ARVC (R)            | 46.2 | 33.4 | 77.0 | 40.4 | 28.4 | 48.0 |
| ARVC (RX)           | 45.1 | 33.1 | 83.8 | 40.2 | 28.4 | 48.1 |
| ARVC (R+RX)         | 49.7 | 34.9 | 91.8 | 42.4 | 29.1 | 50.8 |

Table 3. Autoregressive captioning performance on both MSVD and MSR-VTT datasets, where B@4, M and C are short for BLEU@4, METEOR and CIDEr. Features are denoted in brackets: I$_1$ (Inception-V4 [29]), IR$_2$ (Inception-ResNet-V2 [29]), C (C3D [20]), R (ResNet-101 [20]), RX (ResNeXt101 [19]).
5. Analysis

To complement the aforementioned results, we present analyses that provide some intuition as to why our proposed method works. The effects of knowledge distillation and different number of length candidates $L$ are discussed in supplementary materials due to space limitation. Here are their conclusions. (1) Knowledge distillation is helpful for quick convergence (e.g., $I = 2$ is enough to converge in MSR-VTT dataset), but does not promote the performance. (2) Proper $L$ (e.g., 5) can improve the caption quality.

5.1. Ablation Study and Diversity Study

In this work, we also find “repeated translations” problem [35], which is common for NA models in the context of NMT, and thus simply adopts the de-duplication technique. The effects brought by de-duplication (DD), masking decision (MD) and candidate decision (CD) are shown in Table 4. These techniques can be arranged in order of importance, i.e., CD > MD > DD. The improvement brought by CD and MD indicates that auxiliary scoring information is not only beneficial for selecting suitable candidates but also helpful for NAVC to focus on inappropriate tokens. From another perspective, it shows that higher NAVC’s confidence on a sentence may not reflect its quality. All these findings suggest that an internal auxiliary scoring module is worth exploring in the future to get rid of external constraints.

To analyze the diversity of generated captions, following the literature in image captioning [9], we compute three metrics, namely Novel (the percentage of captions that have not been seen in the training data), Unique (the percentage of captions that are unique among the generated captions) and Vocab Usage (the percentage of words in the vocabulary that are adopted to generate captions). The results in Table 5 indicates that NAVC based on iterative refinement can generate more diverse captions.

### 5.2. Qualitative Examples

Figure 4 visualizes four examples on MSR-VTT test set. It can be observed that NAVC based on iterative refinement has a distinct characteristic, i.e., capturing salient visual information in early iterations whereas gradually correcting grammatical errors in later iterations. For example, only conditioning on the video representation ($I = 1$), NAVC is able to capture “minecraft”, “paper” and “food”, all of which are salient within two presented frames. And these are exactly the information we can get at a glance. Remarkably, NAVC can recognize “wrestlers”, although this word is replaced by “men” later (in our full model) since “two men” is more common than “two wrestlers”. Moreover,
Table 6. The CIDEr score and repetition ratio of tokens (RepR) when decoding with a different \( I \) on both datasets.

| Iteration \((I)\) | MSVD | MSR-VTT |
|------------------|------|---------|
|                  | CIDEr | RepR (%) | CIDEr | RepR (%) |
| 1                | 85.4  | 5.16    | 37.4  | 18.76    |
| 2                | 89.4  | 3.16    | 46.3  | 13.95    |
| 3                | 89.0  | 1.51    | 48.2  | 5.40     |
| 4                | 89.3  | 0.08    | 48.9  | 0.58     |
| 5                | 88.2  | 0.05    | 49.4  | 0.28     |

Figure 5. POS tagging analysis on MSR-VTT test set.

5.3. The Necessity of Iterative Refinement

Based on the discussion in Section 5.2, we further study the effect of iterative refinement. Table 6 shows that iterative refinement drastically reduces the repetition ratio of tokens in the first few iterations. It can be observed that the model reaches performance saturation early in MSVD dataset, thus we are hard to draw conclusions in this dataset. As for the MSR-VTT dataset, the decrease in repetition ratio correlates with the steep rise in CIDEr score, suggesting that iterative refinement is able to relieve “multimodality problem” \([16]\) (which has been introduced in Section 2.2).

Moreover, we utilize the NLTK tool to analyze the POS tagging of captions generated by our full model, as shown in Figure 5. The smooth curve of nouns indicates that NAVC generates most of the nouns, i.e., captures most of the visual information at the first iteration. Combining the decline of the curve of determiner, the repeated token “a” shown in Figure 3 and the decrease in repetition ratio in Table 6, we conclude that NAVC also tends to generate words of high frequency (i.e., determiner) at the first few iterations, resulting in high repetition ratio. Besides, considering the steeply rising curve of gerund (e.g., talking and playing) and preposition (e.g., to and on), linguistic generation is emphasized in later iterations. Therefore, these findings support our claim that iterative refinement enables the model to generate captions in a first visual then linguistic generation manner.

5.4. The Interpretation of Behavioral Differences

NAV C behaves differently in two datasets according to Table 2 and 6, i.e., NAVC converges more quickly in MSVD dataset. We suspect that NAV C confronts a more serious “multimodality problem” in the MSR-VTT dataset. To test our hypothesis, we measure per-position vocabulary usage in training data, which may reveal NAV C’s perplexity on each position, as a proxy metric for the “multimodality problem”. The results shown in Figure 6 match our hypothesis. For example, more than one-quarter words from the vocabulary can be placed at the first position (the start of the sentence) in MSR-VTT dataset, more than twice the proportion in MSVD dataset, making the NAV C more confused when predicting tokens individually. This finding suggests that a larger \( I \) is required if the dataset is more “diverse”, i.e., having higher averaged per-position vocabulary usage.

6. Conclusion

In this work, we present a first attempt to propose a non-autoregressive video captioning model (NAV C) with iterative refinement. With highly parallel supported decoding algorithm and our proposal to exploit external auxiliary scoring information, our proposed NAV C allows for decoding in parallel and producing high-quality captions in just a few cycles. The experimental results show that our method can generate captions in a first visual then a linguistic generation manner, which is more consistent with human intuition than sequential manner and avoids the generated sentences lacking in variability. In particular, the superior improvement brought by external auxiliary scoring information encourages us to explore an internal auxiliary scoring module in the future work to get rid of external constraints.
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7. Supplementary Materials

7.1. Datasets

We evaluate our technique using two popular benchmark datasets from the existing literature in video captioning, namely Microsoft Video Description (MSVD) dataset [17], and MSR-Video To Text (MSR-VTT) dataset [37].

**MSVD Dataset.** It contains 1,970 video clips with an average duration of 9 seconds. Each clip is labeled with about 40 English sentences, resulting in approximately 80,000 description pairs. Following the split settings in prior works [38] [34], we split the dataset into training, validation and testing set with 1,200, 100 and 670 videos, respectively. The resulting training set has a vocabulary size of 9,750.

**MSR-VTT Dataset.** It is one of the largest vision-to-language datasets, consisting of 10,000 web video clips with 20 human-annotated captions per clip. Following the official split [37], we utilize 6,513, 497 and 2,990 video clips for training, validation and testing, respectively. After keeping words appear more than twice, the resulting training set has a vocabulary size of 10,546.

7.2. Implementation Details

**Feature Extraction.** To extract image features, we sample the video at 3 fps for the MSVD dataset whereas 5 fps for the MSR-VTT dataset, and set the maximum number of frames as 60. In terms of motion features, we sample the videos at 25 fps and extract features for every 16 consecutive frames with 8 frames overlap for both datasets. We extract 2048-D image features from ResNet-101 [20] pre-trained on the ImageNet dataset [11], whereas extract 2048-D motion features from ResNeXt-101 [19] pre-trained on the Kinetics dataset [22]. We include the coarse category information for the MSR-VTT dataset.

**Training Settings.** Based on the statistics of training data, we set the maximum sequence length $T_{max}$ as 30 for MSR-VTT dataset whereas 20 for MSVD dataset. To train effectively, we set $K = 8$ for each modality. Assuming we obtained $N_f$ image features, we first divide $N_f$ into $K$ snippets, then randomly/uniformly sample 1 feature from each snippet to achieve $K$ features during training/evaluation process. If $N_f < K$, then we use linear mapping $\frac{k}{K} \times N_f$, $k \in [1, K]$. So is motion features. As for the self-attention based decoder, we use a set of smaller hyperparameters compared with the base configuration [31], i.e., 1 layer per decoder stack ($N = 1$), 512 model dimensions ($d_m = 512$, the same with word embedding size), 2048 hidden dimensions, 8 attention heads per layer. Both positional encoding in the decoder and the category information are implemented by trainable 512-D embedding layer. For regularization, we use 0.5 dropout and $5 \times 10^{-4}$ $L_2$ weight decay. We train batches of 64 video-sentence pairs using ADAM [23] with an initial learning rate of $5 \times 10^{-4}$.
The learning rate decreases at a rate of 0.9 per epoch until it reaches the minimum learning rate $5 \times 10^{-5}$. We stop training our model until 50 epochs are reached and the best model is selected according to the performance on the validation set.

**Evaluation Settings.** We adopt three common metrics including BLEU [26], METEOR [2] and CIDEr [32]. All metrics are computed using the API released by Microsoft COCO Evaluation Server [7]. During iterative refinement procedure, the lower bound of masking ratio $\lambda$ is set to 0.4.

7.3. The Effect of Different Numbers of Length Candidates

In the following experiments, we only report the performance of our full model (NAV$_{mpi}$) for simplicity since consistent conclusions can be achieved by using the base model (NAV$_m$). Figure 7 shows the effect of different numbers of length Candidates $L$ on MSR-VTT dataset, whereas Figure 8 is for MSVD dataset. According to the curve under different $I$, different metrics and different datasets, we can draw a unified conclusion that larger $L$ is beneficial for improving performance, and generally when $L \in [5, 7]$, the saturation of performance can be reached.

7.4. The Effect of Knowledge Distillation

In the context of NMT, knowledge distillation can improve translation quality for non-autoregressive models. Here, we analyze the effect of it in video captioning. To generate the distilled training corpus, we use the well-trained ARVC model to generate 20 captions (i.e., beam size $b = 20$) per training video for both MSR-VTT and MSVD datasets. Figure 9 shows the effect of knowledge distillation on MSR-VTT dataset, whereas Figure 10 is for MSVD dataset. The results show that knowledge distillation can not improve the upper limit of the captioning performance. But however, in MSR-VTT dataset, NAVC with KD only need 2 iterations rather than 5 iterations in the one without KD to reach promising results, i.e., NAVC with KD converges faster in large dataset.
Figure 9. The effect of knowledge distillation (KD) (using the NAVC mpi model) across BLEU@4, METEOR and CIDEr metrics on MSR-VTT dataset. The dashed line in red means the corresponding performance of the autoregressive counterpart.

Figure 10. The effect of knowledge distillation (KD) (using the NAVC mpi model) across BLEU@4, METEOR and CIDEr metrics on MSVD dataset. The dashed line in red means the corresponding performance of the autoregressive counterpart.

7.5. Discussion

Although the proposal of using the external auxiliary scoring information improves the captioning performance (i.e., the performance of NAVC mpi is higher than NAVC mp), the downside of our proposed NAVC mpi lies in the double model size. To conduct a totally fair comparison, we here compare NAVC mp + KD and NAVC mpi, both of which utilize double model size. Specifically, in the former case, ARVC influences the training process of NAVC mpi through knowledge distillation (KD) while influences the inference process of NAVC mp in the latter case. The results in Figure 11 show that NAVC can achieve better performance when the ARVC counterpart is exploited to provide auxiliary scoring information rather than distill the training corpus. So a light internal scoring module deserves to be explored to reduce the memory usage in the future.
Figure 11. Comparison between NAVC + MP + KD (NAVC_{mp} + KD) and NAVC + MP + Interact (NAVC_{mpint}) under METEOR metric on both MSR-VTT and MSVD dataset.