Resnet based Deep Gated Recurrent Unit for Image Captioning on Smartphone

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(First received 21 February 2022 and in final form 30 April 2022)

DOI: 10.31590/ejosat.1107035


Abstract

Image captioning aims at generating grammatically and semantically acceptable natural language sentences for visual contents. Gated recurrent units (GRU) based approaches have recently attracted much attention due to their performance in caption generation. Challenges with GRU are to deal with vanishing gradient problems and modulation of the most relevant information flow in deep networks. In this paper, we propose a resnet-based deep GRU approach to overcome the vanishing gradient problem with residual connections while the most relevant information is ensured to flow using multiple layers of GRU. Residual connections are employed between consecutive layers of deep GRU, which improves the gradient flow from lower to upper layers. Experimental investigations on the publicly available MSCOCO dataset prove that the proposed approach achieves comparable performance with some state-of-the-art approaches. Moreover, the approach is embedded into our custom-designed Android application, CaptionEye, which offers the ability to generate captions without an internet connection under a voice user interface.

Keywords: Gated Recurrent Unit, Residual Connection, Image Captioning, Android Application.

Resnet Tabanlı Derin Geçitli Tekrarlayan Birim ile Akıllı Telefonda Görüntü Altyazılıma

Öz


Anahtar Kelimeler: Kapılı Tekrarlayan Birim, Artık Bağlantı, Görüntü Altyazılıma, Android Uygulama.
1. Introduction

Image captioning focuses on expressing images with linguistically and semantically proper sentences (Fetli, Çaylı, Moral, Kilç, & Aytuğ, 2021; Keskin, Çaylı, Moral, Kilç, & Aytuğ, 2021), which has found applications in visual question answering (Anderson et al., 2018), image indexing (Chang, 1995), and virtual assistants (Aydın, Çaylı, Kilç, & Aytuğ Onan, 2022; Baran, Moral, & Kilç, 2021; Çaylı, Makav, Kilç, & Onan, 2020; Keskin, Moral, Kilç, & Onan, 2021; Makav & Kilç, 2019b). Recent studies mainly benefit from retrieval-based, template-based, and neural encoder-decoder frameworks for image captioning. The retrieval-based framework creates a candidate caption set from reference captions in the dataset similar to the input image. A caption that describes the most semantic information of the input image is selected from the candidate set (Yang et al., 2020). The dependency of the candidate set on the reference captions results in meaningless captions for images different from those in the training set.

The template-based framework predicts tags utilizing subjects, objects, and verbs from the image and then employs predefined language templates to generate a caption. However, the utilization of the framework causes no diversity in the generated captions due to the limited number of templates (Yu, Li, Yu, Huang, & technology, 2019). The neural encoder-decoder framework, which conventionally consists of a convolutional neural network (CNN) and recurrent neural network (RNN), overcomes the issues in retrieval-based and template-based frameworks (Makav & Kilç, 2019a; Mao et al., 2014) because it conveys visual information of images as a latent vector for effective caption generation. In general, many researchers exploit CNN architectures pre-trained on largescale image classification datasets such as Inception-v3 (Szegedy, Vanhoucke, Ioffe, Shlens, & Wojna, 2016), Xception (Chollet, 2017), and NASNet (Qin & Wang, 2019) in the encoder because training from scratch is computationally expensive and time-consuming.

The latent vector is fed to the RNN-based decoder utilizing injection techniques for caption generation. There are four injection techniques for image captioning: init-inject, pre-inject, par-inject, and merge (Tanti, Gatt, & Camilleri, 2018). For the init-inject, the latent vector which contains the image features is fed to the initial state of the RNN (Devlin et al., 2015; Liu, Zhu, Ye, Guadarrama, & Murphy, 2017). The pre-inject employs the latent vector as input to the RNN priorly to the words (Nina & Rodriguez, 2015; Rennie, Marcheret, Mroueh, Ross, & Goel, 2017; Vinyals, Toshev, Bengio, & Erhan, 2015). In the par-inject, the latent vector is concatenated with a word embedding layer output and fed to the RNN as input (Donahue et al., 2015; Yao, Pan, Li, Qiu, & Mei, 2017). The merge adds the latent vector to linguistic features coming from the RNN before the output layer of the decoder (Baran et al., 2021), (Mao et al., 2014), (Mao et al., 2015). RNN is specifically developed to deal with long sequence data. However, as the sequence gets longer, vanilla RNN encounters issues of vanishing and exploding gradients (Bengio, Simard, & Frasconi, 1994; Q. Wang, Bu, & He, 2020). Therefore, gated RNNs such as Long-short-term memory (LSTM) (Hochreiter & Schmidhuber, 1997) and GRU (Chung, Gulcehre, Cho, & Bengio, 2014) have been developed to overcome these issues. LSTM provides high performance in language modeling studies, such as machine translation and captioning, with input, output, and forget gates. GRU combines the forget and input gates into a single update gate, making the GRU utilize fewer parameters than the LSTM. Therefore, GRU-based networks prominently converge on large-scale datasets faster than LSTM-based (Kilç, 2021; B. Wang, Kong, Guan, & Xiong, 2019). Stacking RNN layers improves the network to capture more relevant features, leading to a meaningful caption (Rahman, Srikumar, & Smith, 2018; Sagheer & Koth, 2019). Despite the promising results with multiple RNN layers, retaining the gradient flow becomes challenging due to increased number of layers.

In this study, we propose a resnet-based deep gated recurrent unit approach under the neural encoder-decoder framework for image captioning. The approach employs residual connections between subsequent layers on the decoder side to maintain gradient flow. Inception-v3 CNN architecture pre-trained on the ImageNet dataset is utilized on the encoder side. We used the MSCOCO Captions dataset (Lin et al., 2014) for experiments and evaluated the efficacy with performance metrics such as CIDEr, SPICE, METEOR, ROUGE-L, and BLEU-n (1, 2, 3, 4).

The rest of the paper is organized as follows: Section 2 presents the proposed image captioning approach with theoretical foundations and our custom-designed Android application CaptionEye, which generates a caption without an internet connection. Section 3 introduces the setup of the dataset, performance metrics, and results. Closing remarks are given in Section 4.

2. Methodology

In this section, the proposed image captioning approach under the encoder-decoder framework is first introduced. Then, we present the Android application CaptionEye running the proposed approach without an internet connection.

2.1. The Proposed Approach

We utilize the Inception-v3 CNN architecture to extract the features for a given image in the encoder, and then an RNN based decoder generates a caption in the proposed approach.

The Inception-v3 architecture consists of convolution, pooling, and linear layers and has an input size of 3-by-299-by-299. Furthermore, the output of the global average pooling layer is taken as the image feature, which has a size of 2048.
Then, the feature is passed into the decoder as the latent vector. On the other hand, the decoder consists of embedding, multi-layer GRU, and linear layers. The embedding layer aims to represent the words as meaningful vectors, which founds effective use in language modeling. A GRU is a gated RNN with reset \( r_t \), update \( z_t \), and new \( u_t \) gates. The GRU updates the hidden state as shown in Equation 1.

\[
\begin{align*}
    r_t &= \sigma(W_r x_t + W_r h_{t-1}) \\
    z_t &= \sigma(W_z x_t + W_z h_{t-1}) \\
    h_t &= (1 - z_t) h_{t-1} + z_t u_t \\
    u_t &= \tanh(W_u x_t + W_u (r_t h_{t-1}))
\end{align*}
\]

where \( x_t \) is the input, and \( h_t \) is the hidden state at time \( t \). Similarly, \( W_r, W_z, \) and \( W_u \) are the weights for the reset, update, and new gates, respectively. Furthermore, \( \tanh \) and \( \sigma \) are the activation functions denoted as \( \tanh \), and \( \sigma \), respectively.

\[
\begin{align*}
    x_t^{l-1}, h_t^{l-1} &= GRU_l(x_t^{l-1}, h_t^{l-1}) \\
    x_t^{l+1}, h_t^{l+1} &= GRU_{l+1}(x_t^{l} + x_t^{l-1}, h_t^{l+1})
\end{align*}
\]

where superscript \( l \) represents the order of the GRU layer. Deep GRU consists of multiple GRU layers stacked on top of each other. Residual connections are employed between the layers as shown in Equation (2).

The linear layer consists of weight and bias and outputs a probability distribution over words. \( \hat{Y} = y_1, y_2, y_3, \ldots, y_n \) where \( y_n \) corresponds to the \( n \)-th word which represents a ground-truth sentence. Similarly, \( \hat{Y} \) is the sequential prediction of the approach. The cross entropy loss, a combination of softmax activation function and negative log-likelihood loss (NLL), is utilized in training. Therefore, the loss is calculated as \( \text{loss} = \text{NLL}(\text{softmax}(Y), \text{softmax}(\hat{Y})) \). In addition, the stochastic gradient descent algorithm is utilized for training.

### 2.2. Android-based Application

The developed Android application called CaptionEye offers to generate captions on smartphones without an internet connection, leading to an improved response time. First, the approach is quantized to accelerate the inference time. Then the approach is converted to a script to infer in the application. CaptionEye can take images using the camera or gallery. In addition, it supports various languages with speech command recognition. Screenshots of the CaptionEye are given in Figure 2.

### 3. Experimental Evaluations

This section presents performance evaluations of the proposed approach using the MSCOCO Captions dataset.

#### 3.1. Dataset and Performance Metrics

Here, we evaluate the proposed approach on the MSCOCO Captions as it a large-scale dataset that contains 118287 training and 5000 validation images, and each has at least five corresponding reference captions. We choose six to fifteen word captions in the training set to ensure consistency in the generated caption lengths.
BLEU-n (n = 1, 2, 3, 4), ROUGE-L, SPICE, METEOR, and CIDEr performance metrics are employed to check the accuracy of the proposed approach. BLEU-n measures the n-gram overlap between generated and reference captions developed initially for machine translation. Similarly, METEOR is developed for machine translation and utilizes the harmonic average of unigram matches between precision and recalls. ROUGE-L is a text summary performance metric that measures the longest common subsequence between a generated caption and references. SPICE is a semantic performance metric that first parses each reference sentence and then evaluates the objects, attributes, and relationships in the generated captions, rather than directly comparing a generated caption with a set of reference sentences for syntactic compatibility. CIDEr evaluates the consensus between a caption and references, exploiting sentence similarity to capture gramatical accuracy and saliency concepts. We choose the CIDEr to compare the main findings as it is the default metric in the MSCOCO Captions dataset evaluations.

In Table 1, we present the scores of the proposed approach across multiple performance metrics where "with residual connections" achieves the highest CIDEr score in the 10-layer. However, the approach "without residual connections" reaches its finest in the 5-layer. This discrepancy in the scores could be attributed to the benefits of residual connections.

In Table 2, we report a comparison of the proposed residual connected multi-layer GRU with encoder-decoder approaches. Our proposed approach outperforms (Chen et al., 2018) and (You et al., 2018) in terms of all performance metrics.

Compared with the "without residual connections", the "with residual connections" achieves more accurate caption generation. For the first image of Table 3, the proposed approach generates the caption "a city street with a lot of people walking around it" which is a meaningful description. On the other hand, the caption generated by the "without residual connections" refers to "a large clock tower" which is defective information for the image. Furthermore, "with residual connections" expresses the image as "a kite is flying in the sky" where the phrase "a kite" in the caption causes misinformation because there are two kites in the image. However, "without residual connections" causes wrong knowledge with the phrase "a person standing in a field" by recognizing unfound objects. The results verify that the proposed approach emerges more semantical objects and attributes in the captions.

Figure 2 presents screenshots of CaptionEye. The homepage of the application as shown in Figure 2 (a). The microphone icon on the main screen leads the user to the speech command recognition, as shown in Figure 2 (b). The gallery icon on the main screen allows the user to access the phone gallery shown in Figure 2 (c), while Figure 2 (d) shows the caption generated by the application. The speaker icon on the main screen narrates the generated caption. The three dots icon on the right of the main screen opens the settings window in Figure 2 (e): language selection, application background selection, voice speed, and pitch adjustments. Figure 2 (f) shows the language selection screen. Twenty-one different language options are offered in the application. Figure 2 (g) shows the image capturing screen, which opens with the camera icon on the main page. Figure 2 (h) shows the generated caption with the selected language option.
Reference Captions:
(1) A chinese street with a mcdonalds in the back drop.
(2) People and buses on a city street under cloudy skies.
(3) A large open area with concrete floor and a mcdonalds in the background with chinese writing on the building.
(4) An asian city square, with people, buses, and a mcdonald's.
(5) A red bus driving down a busy city street surrounded by tall buildings.

Generated Captions:
Residual connections: a city street with a lot of people walking around it.
Without residual connections: a crowded city street with a large clock tower.

Residual connections: a kite is flying in the sky.
Without residual connections: a person standing in a field flying a colorful kite.

Table 3. Samples with generated and reference captions

4. Conclusion
In this paper, a residual-connected multi-layer GRU under the encoder-decoder framework for image captioning, has been proposed. The proposed approach includes an Inception-v3 as an encoder for feature extraction of the image and a residual connected GRU-based decoder to generate the corresponding caption. Residual connections carry the features in the multi-layer GRU from lower to upper layers inducing a more valid gradient flow. We evaluated the approach on the MSCOCO Captions dataset, which demonstrated that residual connections performance improved significantly and achieved state-of-the-art performance. Additionally, we developed an Android application named CaptionEye utilizes the proposed approach with a user-friendly interface that has great potential for the visually impaired in daily activities.

5. Acknowledge
This research was supported by the Scientific and Technological Research Council of Turkey (TUBITAK)-British Council (The Newton-Katip Celebí Fund Institutional Links, Turkey-UK project: 120N995) and TUBITAK 2209-B Industry Oriented Research Project Support Programme for Undergraduate Students with project no: 1139B12100443.

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