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The authors declare that they have no conflict of interest or competing interest in this work. N/A

0.3 Availability of data and material (data transparency)

The data-set used in all experiments and results reported in this work is publicly available for download. COCO data-set is available at “cocodataset.org”.

0.4 Code availability (software application or custom code)

The code for some of the papers reviewed in this work were originally published by the authors on github. The reader of this work can lookup for the code for a particular paper reviewed in this work online.

0.5 Authors’ contributions

Zanyar Zohourianshahzadi collected all the research material and wrote the original text of the survey paper. Jugal K. Kalita helped with article preparation phase and provided suggestions regarding the text and structure of the paper.
Neural Attention for Image Captioning: Review of Outstanding Methods

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Abstract Image captioning is the task of automatically generating sentences that describe an input image in the best way possible. The most successful techniques for automatically generating image captions have recently used attentive deep learning models. There are variations in the way deep learning models with attention are designed. In this survey, we provide a review of literature related to attentive deep learning models for image captioning. Instead of offering a comprehensive review of all prior work on deep image captioning models, we explain various types of attention mechanisms used for the task of image captioning in deep learning models. The most successful deep learning models used for image captioning follow the encoder-decoder architecture, although there are differences in the way these models employ attention mechanisms. Via analysis on performance results from different attentive deep models for image captioning, we aim at finding the most successful types of attention mechanisms in deep models for image captioning. Soft attention, bottom-up attention, and multi-head attention are the types of attention mechanism widely used in state-of-the-art attentive deep learning models for image captioning. At the current time, the best results are achieved from variants of multi-head attention with bottom-up attention.

Keywords Image captioning · Attention mechanism · LSTM · Transformer
1 Introduction

Image captioning creates a nexus between natural language processing and computer vision. Image captioning systems could be used for a variety of tasks. Although such systems have been mostly trained on libraries of mundane images such as ones obtained by mining the web, one can easily think of beneficial use cases. For instance, these systems could enable blind individuals to receive visual information about their surrounding environment. When these systems are trained on medical images, they could be used to provide physicians with useful information and help with the diagnosis procedures [78]. Other applications of image captioning include image-sentence search and retrieval as well as bringing visual intelligence for robots. Automatic image captioning can also be used in advanced recommendation and visual assistant systems.

Template generation and slot filling [25,55,63] and caption retrieval [76,31,38,88] are the early techniques used for automatic image caption generation. In comparison with template-based and retrieval methods, better results have been achieved by employing deep neural networks [51,52,48,47]. The common deep learning architecture used is the encoder-decoder [89,16,46] architecture. The encoder-decoder scheme was introduced in the context of neural machine translation. Using the encoder-decoder approach, we can divide the translation task into two parts, the encoding phase extracts features from input data, and decoding phase creates the output with respect to the encoded or extracted features. Deep learning methods learn visual features by employing convolutional neural networks [35,87] (CNNs) or a combination of object detectors [30,29,82] with CNNs. In image captioning, we use the encoder-decoder architecture like how they are used in neural machine translation, since we map visual features to a sequence of tokens, analogous to mapping an input sequence of words to an output sequence for translation. The tokens are the words of a sentence in array before they are used in the process of generating word embeddings. Early deep attentive image captioning models employed convolutional neural networks (CNN) as encoders and long short-term memory networks (LSTM) [37] as decoders [102,14]. In most of the work published recently and reviewed in this survey, bottom-up attention [4] is used for visual feature extraction, which we explain in Section 3.

Image captioning using deep learning usually involves supervised learning. Although recently, Laina et al. [56] and Feng et al. [26] have showed that training a deep learning model for image captioning could lead to desirable results using unsupervised learning, the best results still come from the models trained with supervised learning. Therefore, it is not necessary to categorize the papers reviewed for this survey under supervised learning and unsupervised learning. In supervised learning, we always train the model with a dataset containing examples labeled with the ground truth of the output.

Different types of encoders feed different types of information to the attention mechanisms and language models (decoders). After performing a review of the evolution of attention mechanisms in image captioning, we categorize the state-of-the-art literature based on the types of attention mechanisms used alongside different kinds of encoders such as CNNs or CNNs and object detectors (bottom-up attention encoders) or a combination of these with graph convolutional networks (GCN) [8,20], coupled with various types of decoders, primarily LSTMs [37] and Transformer [93]. The Transformer is an encoder-decoder based model that con-
The task of image captioning using attentive deep learning models employing encoder-decoder architectures. The majority of deep learning models for image captioning use the encoder-decoder architecture.

Our goal in this survey is to review and reveal the best practices in employing attention mechanisms for image captioning in deep neural networks, specifically among the state-of-the-art methods that achieve better performance in comparison with earlier types of attention mechanisms such as spatial soft and hard attention or semantic attention.

In Section 2, we provide a brief review of previous surveys of deep learning models used for automatic image caption generation. In Section 3, we discuss the evolution path of attention mechanisms from earlier methods and how they inspired state-of-the-art literature. In Section 4.1, we offer a performance comparison among the state-of-the-art methods reviewed in our survey.

2 Related Work

Recently several high-quality surveys on image captioning with deep neural networks [39,70] and other techniques such as template generation and slot filling [6,85,64] have been published. Instead of reviewing all methods used for image captioning, we record the success the use of attention mechanisms has brought to image captioning. After briefly reviewing the history of attention mechanisms in image captioning, we review the state-of-the-art literature to highlight the most successful attention mechanisms. This is what mainly differentiates our work from previous surveys on deep learning models for image captioning.

In general, researchers have recently noticed the usefulness of self-attention and multi-head attention over recurrent neural networks. The Transformer [93] model utilizes self-attention (scaled dot-attention) inside multi-head attention to obviate the use of recurrences and convolutions, relying fully on attention for neural machine translation. We provide a brief review of the methods that use the Transformer model or its variants for image captioning as well as other methods that use LSTMs with attention mechanisms.

A comprehensive survey of deep learning models for image captioning by Hossain et. al. [39], creates a well-defined taxonomy for the models. However, the most successful methods published after this paper have used Transformers [93].
or variations of this model. The same applies to the survey by Liu et al. [70]. Although these surveys provide good background on evaluation metrics, datasets and methods used for automatic image caption generation, for the most part they do not discuss the subtle differences among the attention mechanisms used in the deep learning models for image captioning. This is mainly because the methods published after these surveys used bottom-up attention encoders and Transformer or components of this model such as multi-head attention, which improves performance by adding more attention units in a parallel manner. Multi-head attention was introduced by Vaswani et al. [93].

Another survey by Bai and An [6], reviews methods that use deep learning as well as other non-empirical methods. This survey and other similar surveys performed by Sharma et al. [85] and Li et al. [64] on automatic image caption generation do not perform a review of attentive deep learning models for image captioning.

A noteworthy survey by Pavlopoulos et al. [78], reviews deep learning models and other techniques used for medical image captioning. Given a large dataset of medical images and relevant diagnosis sentences for each image, it is possible to train deep learning models used for image captioning to generate candidate diagnosis sentences. This is likely to help physicians and save them considerable time when performing diagnosis procedures using visual medical data. This survey also reviews the datasets used for medical image captioning.

The comprehensive survey performed by Hossain et al. [39], offers useful information regarding common datasets, metrics and categories for deep learning models used for image captioning. We avoid repeating the same information and instead focus on the state-of-the-art models that use attention mechanisms. We also emphasize work that has been published after the previous surveys and offer a new taxonomy for attentive deep learning models used for image captioning.

3 Attentive Deep Learning for Image Captioning

In this section, first we discuss the early use of attention mechanisms in image captioning deep models. We follow by the introduction of bottom-up and top-down attention [3] (Up-Down Attention), which became a source of inspiration for most of the later work. In recent years, the use of generative adversarial networks (GANs) for image captioning has also led to good results [19, 69]. In comparison with the encoder-decoder architecture, which is usually trained with cross-entropy loss, GAN architectures are trained with adversarial loss, making it impossible to perform a direct comparison of performance. Although recently attention mechanism was employed inside a GAN model [110], this model utilizes the encoder-decoder architecture inside the generator and discriminator modules in order to make use of attention. Considering that attention mechanisms have been widely used in encoder-decoder architectures, we present the way attention is calculated and used in these architectures.

After a review of history of attention mechanisms used for image captioning in the context of encoder-decoder architecture, we elaborate upon the state-of-the-art attention mechanisms in the context of different kinds of encoders in which they were used. Different types of encoders provide the attention mechanisms and paired decoders with different kinds of input information. Therefore, it is
necessary to analyze the differences among attention mechanisms in the context of the associated encoders. We have referred to the deep learning models that use attention mechanisms as attentive deep learning models. A taxonomy graph of technologies associated with attentive deep image captioning is illustrated in Fig. 2. In our survey, we focus on attention mechanisms in the context of state-of-the-art encoder-decoder architectures for image captioning.

![Fig. 2 A taxonomy graph of attentive deep learning models used for image caption generation in our survey. Attentive deep learning for image captioning combines computer vision, encoder-decoder architecture and attention mechanism. In our survey, we focus on encoder and decoder types as well as attention mechanisms that are used in the state-of-the-art methods employed for attentive deep image captioning. Bottom-up Attention: Object-Detector + CNN Backbone - MHA: Multi-Head Attention (utilizes Self-Attention) - GCN: Graph Convolutional Networks - LSTM: Long Short-term Memory - Transformer: Employs MHA and Scaled-dot (Self) Attention - NLP: Natural Language Processing.]

3.1 Evolution path of attention for image captioning

We have witnessed the emergence and widespread use of attention mechanisms in deep learning models during the past few years. Attention mechanisms have a long history in neuroscience in the context of visual attention, dating back a few decades [53,22]. A few years ago, attention mechanisms started to show their usefulness in deep learning models in the context of neural machine translation [5]. This led researchers to investigate the usefulness of attention mechanisms in image captioning [102,14]. Fig. 3 shows the seminal works in attentive deep image captioning. In this figure, starting from the left we show the pioneering works in CNNs and encoder-decoder models for image captioning.

CNNs have shown their effectiveness in visual feature extraction in image classification [58,7,59,54]. The pixels in an image have long range dependencies among one another when forming patterns, and therefore CNNs are useful in visual feature
Fig. 3 The timeline of advent of seminal works in attentive deep image captioning. The majority of state-of-the-art attentive methods are inspired by soft and hard attention in Show, Attend and Tell [102] and Bottom-up & Top-Down (Up-Down) Attention [3]. Each block shows the title of work and author name. For more details refer to text.

extraction for image captioning [96,23]. After training a CNN on image classification task on a huge dataset such as the ImageNet [21], we remove the last SoftMax feed-forward layer used for image classification. This mechanism provides us with a CNN backbone that can be used for feature extraction from unseen images. The CNN backbone used for feature extraction among majority of state-of-the-art attentive deep learning models for image captioning is ResNet101 [35].

The first attentive deep model for image captioning was Show, Attend and Tell [102]. This model used a CNN namely the VGG model [87] pre-trained on ImageNet [21] for feature extraction, and LSTM for language modeling as the decoder. This was very similar to other encoder-decoder (CNN-LSTM) architectures for image captioning [96,23,47], except that Show, Attend and Tell [102] employed two variants of attention mechanisms, namely soft and hard attention on the spatial convolutional features to provide a set of attended features for the LSTM decoder that acts as a language model.

In Fig. 3, we do not show the advent of Transformer [93] and Resnet [35] since it would increase the complexity of this diagram. It is important to note that Up-Down attention model utilizes Faster-RCNN [82] with ResNet101 [35] as bottom-up attention for visual feature extraction and high-performing state-of-the-art models have used the bottom-up attention with multi-head attention in Transformer model for image captioning rather than using the traditional attentive LSTM decoder.

In this section, we present work that introduced attention mechanisms as well as other work that became a source of inspiration for most recent deep attentive models for image captioning until the advent of Up-Down attention model. We finish this section by introducing the Up-Down attention model and then start the
next section by exploring state-of-the-art literature categorized based on the kinds of encoders and decoders within which attention is deployed.

In Fig. 4 we show the models that utilize LSTM with attention mechanism on extracted visual features as well as models that use Transformer encoder on extracted visual features from a CNN backbone, and Transformer decoder that receives a masked embedding of the ground truth caption sequence while training. This figure can be applied to all the methods we explain in Section 3.1 and Section 3.2.1 from a general viewpoint.

3.1.1 Soft & Hard Attention

In the Show and Tell model introduced by Vinyals et al. [96], the extracted visual features from a CNN enhanced with batch normalization [42] are passed to an LSTM network for hidden state initialization, whereas in the Show, Attend and Tell model introduced by Xu et al. [102], the set of attended extracted visual features are concatenated with an embedding of each word in the caption sentence at each time step to form the input for the decoder. Applying attention mechanism on visual features and passing the attended visual features to the LSTM decoder would enable it to attend over particular regions in the input image and the word embeddings concurrently. Both models use a feed-forward layer as an embedding layer for a one-hot vector representing the words in the caption sentence from a vocabulary.

Word embeddings are vector representations of the tokens that are fed to a deep learning model. Training simultaneously on word embeddings and attended visual features creates the ability to learn patterns for the words in a sentence and visual features in a shared embedded space. The most common embedding systems used for natural language processing and image captioning are Glove [80] and Word2vec [74]. An easier approach used sometimes is a one-hot vector of the current word in the sentence as input with a size equal to the length of vocabulary. An embedding (feed-forward) layer is then used to encode the one-hot vector into word embeddings. Recurrent neural networks such as long short-term memory networks (LSTMs) [37] and gated recurrent units (GRUs) [15] as well as Transformer [93] can be used for mapping embedded words to visual features for image caption generation.

The LSTM decoder with attention in Show, Attend and Tell receives the set of attended visual features ($\hat{z}$) from an attention function ($f_{att}$), which may either be a soft deterministic or a hard and stochastic function. The LSTM decoder also
receives $E(y_{t-1})$, the word embedding of the previous word in the caption sentence at each time step, and the previously generated hidden state $(h_{t-1})$ created by the LSTM in order to create the next hidden state used for generating the next word at time step $t$.

The attention values ($e_t$) are created by the attention function ($f_{att}$), which is a linear transformation layer that receives the previous state ($h_{t-1}$) and the extracted visual feature vectors $(a_i)$, where each annotation vector $(a_i)$ is a spatial feature vector referring to a specific part of the input image. The final soft weighting vector ($\alpha_t$) is created from application of SoftMax function over the attention values ($e_t$). After the soft attention weights ($\alpha$) are computed we can apply them to the set of extracted spatial visual features in soft attention function ($\phi_{soft}$). At each time step, the soft attention weights ($\alpha$) are multiplied by the feature vectors $(a)$.

The hard attention function ($\phi_{hard}$) employs a one-hot vector $s_t$ parametrized by the weighting vector ($\alpha$). At each time step $t$ the i-th location in the one-hot vector ($s_{ti}$) is set to one if the i-th location in the image is the one being used for feature extraction. This way the model only attends over one annotation vector ($a_i$) rather than a group of weighted annotations as in soft attention.

Both soft and hard attention may be used to calculate the set of attended visual features ($\hat{z}$) for use in an attentive LSTM for generating the hidden state used for caption word prediction. For word generation at each time step by the model the hidden state is calculated by the LSTM decoder in the model, which receives a concatenation of attended visual features ($\hat{z}$) with the hidden state vector generated at previous time step ($h_{t-1}$) and an embedding of the previously generated caption word ($Ey_{t-1}$).

It is important to note that both soft and hard attention mechanisms rely on spatial features extracted from the 2-dimensional image. Considering that an image is represented using three color channels (Red, Blue and Green), the extracted annotation vector contains features extracted from each color channel in a 3-dimensional spatial feature vector. After the set of attended spatial features is calculated, they are ready for use in the attentive LSTM for calculating the next hidden state. The optimization techniques used in Show, Attend and Tell were RMSprop [91] in Flickr30k [112], and ADAM [50] in MS-COCO [67]. We suggest that the readers refer to published literature cited in this work for additional technical details such as how the objective functions for soft and hard attention differ or how the one-hot vector ($s_t$) for hard attention is calculated using a Multinoulli distribution.

The use of attention mechanism greatly improved the performance of the Show, Attend and Tell model compared to Show and Tell. The soft visual attention mechanism that was explained here was used for describing video and image content and translation by Cho et al. [13] in a similar way it was used here except that the attention values from current time step are sent to the attention function for calculating the attention values for the next time step. Yang et al. [106] and Xu et al. [103] created stacked spatial attention models in order to improve soft attention for visual question answering (VQA). In these models, the stacked attention values are calculated based on attended extracted features modulated by the lower-level attention values. Soft and hard visual attention have been a source of inspiration for a most of the state-of-the-art literature. The downside of using spatial features
from the whole image for attention is that fine-grain details from objects and their correlations are not considered.

### 3.1.2 Semantic Attention

Using semantic information for image captioning with encoder-decoder architecture was explored earlier [44]. Introduced by You et al. [111], the main idea behind the introduction of semantic attention was to find a way to consider semantic attributes discovered in the input image for attention calculation. Various techniques can be used for attribute detection such as using weakly annotated images on the web with hash tags and captions. However, the best method for attribute detection turned out to be using a Fully Convolutional Network (FCN) [71], like the work by Fang et al. [24].

The attentive LSTM with semantic attention receives soft-weighted embeddings of attributes for input and output attention models. Inspired by soft attention, the semantic attention creates a set of soft-weighted attention values for the input attention model ($\phi$) by incorporating the embeddings of extracted semantic attributes with an embedding of previously generated word by the model.

The set of extracted visual features ($v$) is provided by the last convolutional layer of the GoogleNet model [90]. Like Show and Tell [96], the extracted visual features are fed to an LSTM for hidden state initialization. The extracted visual features are passed through a linear transformation layer. The output attention model ($\phi$) receives the hidden state generated by the attentive LSTM shown as well as the embeddings of extracted semantic attributes.

The input attention model ($\phi$) creates the input ($x_t$) for the LSTM at each time step. The input attention model applies a set of attention values ($\alpha$) to the set of attributes ($y$) in a soft fashion like soft attention. The set of attention values ($\alpha$) is calculated using a bilinear function over one-hot representations of previously predicted words and attributes. The attention values are then used for normalizing attributes in a SoftMax fashion. A weight matrix is applied to the sum of embeddings of attributes soft-weighted by the attention values that are projected using a diagonal matrix and added to the embedding of previously predicted word.

The output attention model ($\phi$) creates the output of the model ($p_t$) based on the exponent of a projection of the current hidden state added to the sum of attention values ($\beta$) multiplied by the embeddings of attributes passed through a sigmoid gate and projected by a diagonal matrix. The attention values ($\beta$) are calculated by multiplying the current hidden state multiplied by a linear transformation (projection) of embedding of each attribute passed through a sigmoid gate.

Semantic attention has showed better performance compared to visual spatial soft and hard attention. Inspired by semantic attention, Yao et al. [109] employed attributes as semantic information to model the attention to the locally previous words instead of using attributes as complementary representations. Instead of using discovered attributes as semantic information, Mun et al. [75] introduced the text-guided attention model, where a guidance caption is randomly selected among relevant captions gathered from similar images that were found using the nearest neighbor algorithm. Text-guided and semantic attention are similar in that they both calculate attention with respect to textual information related to the
image. They are also different in that text-guided attention uses captions directly as source of attention for guiding the visual attention. Zhou et al. [114] introduced text-conditional attention, which models text-conditional features as a text-based mask on image features. This way text-conditional features are considered as semantic information. Inspired by the soft attention and semantic attention, Chen et al. [10] introduced the spatial and channel-wise attention, where channel-wise attention resembled the semantic attention regarding what should be looked at without discovering the attributes and instead utilized spatial features. The downside of semantic attention is that the quality of generated captions highly relies on the quality of detected attributes from the input image. Additionally discovering attributes from the image requires more external resources, which leads to increased complexity of the model.

3.1.3 Spatial & Channel-wise Attention

Both soft and hard attention in Show, Attend and Tell [102] operate on spatial features. In spatial and channel-wise attention (SCA-CNN) model, channel-wise attention resembles semantic attention because each filter kernel in a convolutional layer acts as a semantic detector [10]. In SCA-CNN [10], the caption word \(y_t\) is generated by mapping the probability vector \(p_t\) to a dictionary. The probability vector \(p_t\) is calculated by applying a SoftMax activation on the hidden state generated by the attentive LSTM \(h_t\) and an embedding of the previous word generated by the model \(y_{t-1}\). The hidden state at each time step \(h_t\) is calculated by the LSTM which receives the concatenation of generated hidden state at previous step and spatial and channel-wise attended visual features \(X_L\) and an embedding of the previous word generated by the model \(y_{t-1}\).

The attended features \(X_L\) are gathered across all convolutional layers, where \(L\) is the total number of layers. The spatial and channel-wise attended visual features \(X^l\) from each layer \(l\) are calculated by applying a modulation function \(f\), which is an element-wise multiplication function between extracted attended features \(CNN(X^l-1)\) from the previous convolutional layer and current attention values \((\alpha, \beta)\) for spatial and channel-wise attention mechanisms \(\Phi_s, \Phi_c\).

The visual features \(V\) for spatial attention are reshaped by flattening width and height, where each visual feature vector \(V_i\) is the visual feature of the \(i\)-th location. The visual features are also reshaped before input to channel-wise attention. Specifically, each vector \(v_i\) in reshaped features is the \(i\)-th channel in visual features \(V\) and the length of the reshaped features is equal to the number of channels. Considering the reshaped features \((V, v)\) for spatial and channel-wise attention, the soft attention values for spatial \((\alpha)\) and channel-wise attention \((\beta)\) are calculated by applying a SoftMax function over the linear transformation of attention values that are calculated via applying a Tanh function over the result of element-wise addition between linear transformations of reshaped features and hidden state generated at previous time step.

Considering spatial and channel-wise attention, we can calculate the attended features in two different ways. We can either calculate spatial attention and use it to modulate the visual features for use in channel-wise attention (spatial-channel) or we can calculate the channel-wise attention and use for modulating the visual features for spatial attention (channel-spatial).
In SCA-CNN, the best results were achieved when channel-wise attention was used for modulating spatial attention inside two layers of ResNet101 (res5c & branch2b). Spatial and channel-wise attention showed better performance compared to Show, Attend and Tell and semantic attention models. Spatial and channel-wise attention are powerful since they can guide the LSTM to where to look at (spatial) and what to look at (channel-wise). The idea of when to look at the visual features and when to rely on textual information for caption word prediction was introduced by Lu et al.\[72\], which we discuss next. Like Show, Attend and Tell, all these models rely on spatial visual features directly without considering the object level details and relationships.

3.1.4 Adaptive Attention

As mentioned earlier, the idea behind adaptive attention is to find a way for the model to know when it should focus on visual features and when it should focus on textual features for caption generation. Unlike Show, Attend and Tell, instead of passing the attended visual features calculated based on the previous hidden state to an LSTM for caption word generation at each time step, adaptive attention receives the current hidden state and the adaptive context vector to be passed through a non-linear function for caption word prediction.

The adaptive context vector (\( \hat{c}_t \)) is calculated based on the attended spatial feature context vector (\( c_t \)). The attended spatial context vector is calculated via soft-weighting applied to visual features (\( V = [v_1, v_2, ..., v_k] \)) modulated by attention values that are obtained via applying a SoftMax function over the result of linear transformations of the set of visual features and the hidden state of LSTM added together and passed through a nonlinear transformation layer.

The visual sentinel (\( s_t \)) is achieved by applying a sentinel gate (\( g_t \)) to the memory of LSTM (\( m_t \)) passed through a Tanh function. The sentinel gate (\( g_t \)) is achieved via applying a sigmoid function over the linear transformations of concatenation of the embedding of the previously generated word (\( E y_{t-1} \)) and global features vector (\( V \)) added to the linear transformation of previously generated hidden state (\( h_t \)). After the visual sentinel is calculated based on the sentinel gate it is ready to be included in adaptive context vector.

A new sentinel gate (\( \beta \)) is included in the adaptive context vector, which is a scalar between 0 and 1. The final sentinel gate (\( \beta \)) decides whether the spatial features context vector should be used, or the visual sentinel (\( s_t \)) should be used to form the adaptive context vector. The final probability over the words in the dictionary is calculated based on a SoftMax feed-forward layer applied to adaptive context vector added to the hidden state vector.

Adaptive attention showed competitive performance compared to other types of attention mechanisms. Like semantic and visual soft and hard attention mechanisms, adaptive attention does not consider object-level details making it hard to know if the model is actually looking at the correct object in the image for word prediction. Inspired by adaptive attention and Up-Down attention, Lu et al.\[73\] introduced the NBT model that could generate captions, which include words that are visually grounded to particular regions in the image. The visual sentinel in adaptive attention is used in NBT and then two pointer vectors\[95\] are used for category and subcategory detection for each word that is grounded in the image.
3.1.5 Bottom-up & Top-down Attention

The idea of incorporating regional features for attention mechanism was explored before the advent of Up-Down attention. Jin et al. [27] discover the regions related to objects in the image using a selective search technique [92]. The regions are filtered with a classifier, and then resized and encoded using a CNN for input to a soft attention mechanism for image captioning. In Areas of Attention model, Pedersoli et al. [79] use spatial transformers [43] and edge boxes [117] for detecting important regions related to objects in the image for feature extraction. In Global-Local Attention model [62], like in Up-Down attention model, Faster-RCNN [82] is used for detecting salient regions in the image for feature extraction, where the global features are extracted from the image as a whole and used in a soft attention mechanism along with local features extracted from object detection regions.

In Up-Down attention model [3], global features are not considered and instead a mean-pooled average of features from each detected region (bounding box) is considered for the Top-Down soft attention mechanism. A non-maximum suppression for each object class using an IoU threshold is performed. Regions with class detection probability that exceeds certain confidence threshold are selected for feature extraction. Employing Faster-RCNN in this fashion creates a Bottom-up hard attention mechanism as only a small number of bounding box detections are considered for feature extraction. In Up-Down attention model, Resnet-101 [35] is used in conjunction with Faster-RCNN for feature extraction from bounding box detections.

The captioning model in the Up-Down attention model consists of two LSTMs. The first LSTM acts as a top-down visual attention model, where the hidden state of the first LSTM is passed to the attention mechanism for generating the set of attended visual features ($\hat{v}$) calculated based on the set of visual features extracted by bottom-up attention. The input for the attention LSTM contains the mean-pooled image features ($\overline{v}$) from each region feature ($v_i$) extracted by the Bottom-up attention concatenated with an embedding of previously generated word and the previous hidden state of the second LSTM that acts as a language model.

After the hidden state of the attention LSTM is calculated based on input, it is ready to be used for calculating the set of soft attention values ($\alpha$). The set of soft attention values are achieved via applying a SoftMax function over the attention values that come from the result of a non-linear transformation of visual features from regions and the hidden state of the model at previous time step passed through linear transformation layers.

The set of attended visual features is calculated based on a soft-weight modulation of attention values over set of extracted visual features. After the set of attended visual features is calculated it is ready to be concatenated with the current hidden state of attention LSTM to form the input for language LSTM. After the hidden state of language LSTM is created based on input, it is passed to a feed-forward SoftMax layer to create the conditional distribution over possible output words.

The Up-Down attention model has become a source of inspiration for most of the state-of-the-art image captioning models as the quality of generated captions are superior to other models that do not use the bottom-up attention.
3.2 Attention with Various Encoders & Decoders

In this section, we explore the state-of-the-art attentive models for image captioning that have been published around the same time and after the advent of Up-Down attention model. The reason is that Up-Down attention model produced competitive results under all image captioning metrics compared to the models published earlier, and therefore it can be considered as baseline for comparison with state-of-the-art models.

3.2.1 CNN Encoders & Attentive Decoders

There are a few state-of-the-art models reviewed in this survey that use the traditional CNN encoder, only using a CNN for feature extraction over the input image as whole. Fig. 4 shows the general framework for models that employ CNNs for feature extraction alongside an attentive decoder for image captioning. The Recurrent Fusion Network model proposed by Jiang et al. [45], is an example of using only a CNN backbone as the encoder part of the model and utilizing attentive LSTM as the decoder. This model employs multiple CNN networks for feature extraction, where the extracted features are sent to multiple LSTMs in the first fusion stage to create the soft multi-attention mechanism. The average of hidden states from LSTMs in the first fusion stage is sent to LSTMs in the second fusion stage alongside multi-attention values. The attention values from each stage are concatenated to form the multi attention values. The hidden states of LSTMs in the second fusion stage are used in a soft-attention mechanism used in LSTM unit as decoder.

Ye et al. [110], employ a linear transformation attention mechanism that applies soft attention on the features coming from the encoder. This is done by using a feed-forward soft attention module that receives the extracted features from the CNN backbone, followed by the application of the attended information to the hidden state of the attentive LSTM decoder for additional information refinement. Similarly, Chen et al. [12] used two parallel linear transformations, joined with element-wise multiplication.

The captioning model introduced by Shuster et al. [86] considers different personality categories while generating captions, thus resulting in personalized captions that carry certain sentimental information. For this purpose, a CNN (ResNet 32 × 48d [101]) is used as image encoder and a linear transformation of personality vector is used for encoding personality information. In the decoder, LSTM is used like how it was utilized in Show and Tell, Show Attend and Tell, and the soft top-down decoder in Up-Down attention model as caption decoders. They achieve the best results from the soft top-down attention decoder in Up-Down attention model. The visual information is used in soft spatial attention like in Show, Attend and Tell. The embedding of personality trait is used as additional input for LSTM in the decoder. This model employs ResNet152 and ResNext32 × 48d as image encoders and thus the results of their experiments are not directly comparable to other methods enumerated in Table 4.1. As mentioned earlier, most of the state-of-the-art methods use ResNet101 or Faster-RCNN with ResNet101 as image encoder.

Different from conventional soft attention mechanisms used with recurrent units, the Transformer [93] model employs scaled-dot (self) attention inside multi-
head attention units eschewing recurrence and convolutions and instead fully relies on attention for sequence generation.

In this survey, among the models that use the Transformer model for image captioning, the attentive model introduced by Zhu et al. [116] is the only one that uses a CNN as encoder. The model introduced by Zhu et al. [116], employs the Transformer’s decoder with a CNN followed by non-linear transformation. The CNN is used as the encoder instead of the original encoder in the Transformer [93] model. The CNN backbones used for feature extraction in this method are ResNet152 and ResNext101, making it hard to perform a direct comparison with results of other methods enumerated in Table 4.1.

All the methods mentioned above achieve good results under captioning metrics since they employ novel ideas in terms of employing soft and multi-head attention in various new ways. The downside with these models is that they all rely on global features extracted from the input image using a CNN and they do not leverage bottom-up attention, which provides object-level details.

CNNs have also been used as language models rather than LSTMs. Aneja et al. [4] use a soft attention mechanism on word embeddings of previously generated words and features from a convolutional encoder to form the attended features for use in convolutional decoder. Although this model showed that convolutional networks can be used as a language model, the results from this model are not competitive in comparison with the results from other state-of-the-art models.

3.2.2 Bottom-up Encoders

Most of methods reviewed in our survey employ bottom-up attention [3] as the encoder. Fig.3 shows the general framework for models that employ bottom-up attention for feature extraction alongside an attentive decoder for image captioning. Previously, we discussed the relationship between the bottom-up and top-down attention model introduced by Anderson et al. [3] and the attentive model used for visual grounding introduced by Lu et al. [73]. Wang et al. [99] introduced a hierarchical soft attention module that considers semantic information (concepts), bottom-up features and convolutional features extracted from equal sized patches in the image. The attention values from different sources are combined with each other using a Multivariate Residual Module to be used by the language LSTM.

Inspired by adaptive attention [72], Gao et al. [28] introduced the deliberate attention. In deliberate attention network the previously generated hidden states of first and second residual LSTMs and global CNN features along with an embedding of caption word are fed to the first residual LSTM, which acts as an attention LSTM in top-down attention module. A linear transformation is applied to the concatenation of current hidden state of first residual LSTM and caption word embedding. The results of this linear transformation layer is sent to the attention layer along with bottom-up features. The attended visual features are sent to the second residual LSTM, which acts as hierarchical attention LSTM, along with the results of linear transformation layer. Adaptive attention is then applied on the hidden state of second residual LSTM and regional features using a visual sentinel. the visual sentinel is calculated based on linear transformations of the output of previous residual layer, global features, attended regional features and previously generated hidden state of second residual LSTM. A concatenation of the results of adaptive attention along with hidden state of second residual LSTM and linear
transformation of caption word embedding and hidden state of first residual LSTM are used in SoftMax function for next caption word generation.

Ke et al. [49], employed a bottom-up attention encoder with a reflective decoder. The reflective decoder module includes a reflective attention module that employs soft-attention and a reflective position module for alignment. Qin et al. [81] introduced an attentive model like the bottom-up and top-down attention model [3]. Instead of only considering the current attention values, the attentive model proposed by Qin et al. [81] also considers the attention values from previous iteration as well as the attention values from current iteration. Huang et al. [41] introduced the adaptive attention time model that allowed the top-down attentive decoder to perform attention in the decoder multiple times as adaptively as required by the model.

Yang et al. [105] employ the idea of adding a control unit before the language model LSTM. This control unit is used for selecting the data source. At each time step, the model adaptively learns how much of the information about attributes, visual features and relationships must be used. Wang et al. [98] employ a recall unit that imitates the way the human brain recalls previous experiences when generating captions for images. This is done by adding a text-image matching unit. The image features and textual features are embedded into a common space, and the cosine similarity between them is calculated. This way a corpus of text is generated for each image from the training data that includes the captions for each image. The recalled words are gathered from the corpus. This allows the model to learn the best sentence structure.

A novel Copy-LSTM unit was introduced by Sammani et al. [84]. Their attentive image captioning model titled as Show, Edit and Tell has a very similar design to Up-Down attention model. They use the bottom-up attention features for a modified soft top-down attention decoder which includes an LSTM based denoising auto-encoder along with the Edit-Net. The Edit-Net includes the top-down attention LSTM and Copy-LSTM which is replaced with the language LSTM in top-down attention module. The Copy-LSTM unit allows the model to adaptively select and copy the memory state of the caption encoder LSTM with the highest soft attention values. Rather than directly modulating the soft attention values on all context (memory) or hidden state as in conventional attention mechanisms, the selective copy mechanism chooses the memory state with the highest value in the corresponding soft attention values. This way the model is able to copy certain
words from the input caption and edit the output caption based on the copied word.

Zhou et al. [115] introduce a novel Part-of-Speech (POS) enhanced image-text matcher to act as a reworder and an attention driver. Soft attention mechanism is used in both the neural caption generator and POS enhanced image-text matching modules. A gated recurrent unit (GRU) is used in the image-text matching module and the attention network is applied on the output of the GRU unit. In the neural caption generator module, an attention network is applied to the visual and textual features. An LSTM is then used as a language model to map the attended features to textual embeddings in a common space.

At this time, bottom-up attention turns out to be the best kind of encoder used for image captioning as it considers object-level details and relationships. However, models that employ only bottom-up attention as encoder do not consider semantic information and spatial relationships. For this reason, graph convolutional networks (GCNs) have been employed with bottom-up attention to provide semantic information and spatial relationships for the attentive language model.

### 3.2.3 Bottom-up & GCN Encoders

A new trend among the state-of-the-art methods is to employ bottom-up attention and GCNs to form the attentive encoder. Fig. 6 shows the general framework for models that employ GCNs with bottom-up attention for image captioning. Inspired by how the SPICE [2] metric is calculated based on a scene graph generated from the input image, graph convolutional networks (GCNs) have been used to extract information from scene graphs.

Yao et al. [107] employed bottom-up attention to provide the salient regions for use in two GCNs for spatial and semantic graphs, applying soft attention on features extracted jointly from these graphs. Wang et al. [97], like the Up-Down attention model, used soft top-down attention, where the soft attention is applied on features extracted from a spatial-semantic scene graph and image regions using the hidden state of attention LSTM. Yao et al. [108] use the Up-Down attention model and GCN-LSTM [107] with a proposed hierarchical parsing module. The hierarchical parsing module leverages Faster-RCNN [82] and Mask-RCNN [34] for detecting and segmenting the set of object regions and instances.
The output of hierarchical parsing module is used in a soft top-down attention to form the output of the model using the language LSTM unit. There are also models that utilize scene graphs alongside bottom-up attention features without employing GCNs. For instance, the attentive model introduced by Li & Jiang [65] employs bottom-up attention features and scene graph information represented in the form of semantic relationship features. The semantic relationship features, and the bottom-up attention features are used to form the input to soft attention in the attentive decoder. Yang et al. [104] introduce a novel scene graph auto-encoder to be used in encoder-decoder model. First, a scene graph auto-encoder is proposed that learns the shared dictionary, which includes the language inductive bias from sentence-to-sentence reconstruction via employing scene graphs. Then they proposed and used a multi-modal graph convolutional network to re-encode visual features using a shared dictionary. The dictionary is shared between scene graph auto-encoder and re-encoder module in encoder-decoder caption generator that receives visual features extracted via CNN. Like top-down attention in Up-Down model, soft attention is used for sentence reconstruction.

Although adding scene graphs or GCNs to bottom-up attention successfully leverages spatial and semantic relationships and achieves better performance compared with Up-Down attention model, these methods suffer from increased model complexity in comparison with models that employ bottom-up features with multi-head attention in the Transformer model. The attention calculation becomes more computationally expensive as the attention values are calculated based on semantic and spatial relationship features alongside bottom-up features. As opposed to utilizing GCNs and scene graphs with bottom-up features for attention, using bottom-up features in scaled-dot attention, which is a component of multi-head attention, achieves better performance and is computationally less expensive due to parallelism in multi-head attention.

3.2.4 Bottom-up & MHA Encoders

Multi-head attention (MHA) that relies on multiple scaled-dot (self) attention heads, was shown to be effective in the Transformer model [93] for neural machine translation. Multi-head attention was used to form both the encoder and decoder. Fig. 7 shows the general framework for models that employ multi-head attention to form the encoder and decoder for image captioning.
Herdade et al. [36] used object names as attributes to be added as input information for the attentive encoder. Yu et al. [113] introduced an attentive model that employed multiple copies of the object detector to provide the bottom-up attention encoder with various sets of object detections. Liu et al. [68] similarly employ cross-modal information for this purpose. Cornia et al. [18] introduced the Meshed-Memory Transformer networks. The Meshed-Memory Transformer networks are similar to the original Transformer networks, except that the self-attention module is augmented with memory slots as plain learnable vectors that can be directly optimized using optimization techniques such as stochastic gradient descent methods. Also, the memory states of each encoder in the encoder stack is connected to all other decoders in the decoder stack using a mesh network connection followed by sigmoid activation. Li et al. [60] introduced the Entangled Transformer encoder and used it for both visual and semantic information to form the input for a multi-modal Transformer decoder. Instead of creating a mesh network connection between the memory states in Meshed-Memory Transformer [18], this model creates a mesh network connection between different queries at different time steps.

Huang et al. [40] introduced the Attention-on-Attention network (AoA-Net) model. In this model, the encoder contains bottom-up attention and a refining module for bottom-up features, which includes multi-head attention followed by AoA module. The decoder includes AoA module on top of an attention LSTM. The AoA module applies a sigmoidal gate on the query concatenated with the output of lower attention module, which could be multi-head attention or attentive LSTM, the result of concatenation is passed through a linear transformation before applying the sigmoidal gate. The final result of the sigmoidal gate is multiplied by another linear transformation of the concatenation of the query and attention values. Pan et al. [77] improved the multi-head attention in Transformer model by adding a bilinear pooling mechanism to the self-attention used inside multi-head attention. Using this mechanism, they introduced the x-linear attention block. The x-linear attention leverages on both the spatial and channel-wise bilinear attention values to extract the interactions between the input features [77]. The X-Linear attention block is used inside a multi-head attention module, which is placed on top of another x-linear attention block that receives the bottom-up features. At each level, the output of x-linear blocks is embedded using linear transformation and the final output of multi-head attention with x-linear attention heads is sent to the next x-linear attention block, which is placed on top of an LSTM. The output of LSTM and x-linear attention are embedded using linear transformation and sent to a feed-forward SoftMax layer for probability vector generation used for caption word generation at each time step. In Table 4.1 We report the result of the experiments with x-linear attention used inside Transformer and multi-head attention with LSTM in x-linear attention network (X-LAN). Guo et al. [33] introduced the normalized self-attention and the geometry-aware self-attention block that considers geometrical information discovered from the visual features. Using a 4-dimensional vector containing the relative position and the size of the bounding boxes for the objects, the relative geometry features between objects are discovered.

At the current time, the best results for image captioning come from models that employ scaled-dot and multi-head attention over bottom-up features and semantic information. In comparison with models that employ GCN-LSTM archi-
tectures, multi-head attention-based methods achieve better performance, making them suitable for best practice when employing attention mechanisms for image captioning.

3.3 Evaluation Metrics

In order to understand the quality of generated captions, automatic metrics are used widely. The survey by Liu et al. [70] offers useful details and information regarding how the evaluation metrics are designed. Therefore, we avoid reiterating the same information here. Without the need for manually verifying the quality of captions by a human agent, automatic metrics such as BLEU [1], METEOR [57], ROUGE [66], CIDER [94] and SPICE [2] provide excellent insight regarding the quality of captions, from different viewpoints. In order to perform a fair comparison of methods, we do not report the results under the ROUGE metric as this metric is not commonly used in the majority of literature we discuss in Section 4.1.

Originally designed for the evaluation of natural language generation tasks such as translation, BLEU, METEOR and ROUGE, provide numerical evaluation of the quality of translation from the input sequence to the output sequence based on n-gram overlap with ground truth translations. Visual information is not considered when creating scores for these metrics and only the textual information regarding the input sequence and output sequence is considered.

The BLEU metric counts and compares the number of occurrences of n-grams in ground truth (reference) caption and generated caption by the model. The initial evaluation precision can be calculated by dividing the number of n-grams in the generated caption that match the n-grams in the ground truth caption, by the length of generated caption (or translation). However, here the translation recall rate is not considered for certain meaningful and rare words, which leads to meaningless sentences achieving high precision score. To address this problem, the n-grams are first counted in the generated caption sentence, then the maximum number of n-grams is counted in each ground truth sentence. The minimum value between the number of occurrences of n-grams in ground truth caption and generated caption by the model matching each other and the maximum number of n-grams in each ground truth sentence is considered as the number of n-grams matching each other. Because n-grams (usually between 1-4) are used for calculating the precision, therefore short sentence can highly affect the precision. To address this problem a brevity penalty was introduced. The brevity penalty is set to one if the length of generated caption is longer than the length of ground truth caption. If the length of ground truth caption is longer than the generated caption the brevity penalty is set to the exponential of one minus length of generated caption divided by the length of ground truth caption. Finally, BLEU is calculated via multiplying the brevity penalty to the exponential of average of log precision for different n-grams (1-4) resulting in BLEU1, BLEU2, BLEU3 and BLEU4 metrics.

The Meteor metric is calculated based on weighted average of single-precision rate and word recall rate. In order to perform synonym and stem and word matching, Meteor calculates the value and recall rate of $F_{mean}$. The average $F_{mean}$ of recall and precision accuracy between the best candidate captions and ground truth captions is calculated via multiplying precision and recall divided by a constant value (usually around 3) multiplied to precision plus one minus the same
constant value multiplied to recall rate. A penalty factor is introduced via multiplying a constant value (usually around 0.5) to the square of number of chunks divided by the number of uni-grams. Finally, the METEOR metric is calculated by multiplying one minus the penalty factor multiplied to the $F_{mean}$.

To overcome the issue of not being able to consider visual information for generating automatic metric scores, Vedatanam et al. [94] introduced the CIDER score. By employing term frequency and inverse document frequency (TF-IDF), this metric evaluates the quality of a set of candidate sentences with a set of ground truth sentences, given an input image. For the first time, this metric provided a way to evaluate the quality of generated captions considering fluency and relevancy; fluency in caption sentence, and relevancy between the caption sentence and input image. The CIDER score is achieved via calculating the n-gram occurrences that match between the generated caption and ground truth captions. Based on TF-IDF the n-grams are weighted and used for representing sentences in vector space. The cosine similarity between the generated and ground truth sentence (TF-IDF) vectors is considered as CIDER score. Although the CIDER metric was successful in assessing relevancy between the images and sentences, there was no way to verify the existence or truth regarding the presence of spatial relationships among the objects in the given image, as described in the caption sentence generated by a model.

To improve the quality of assessment, Anderson et al. introduced the SPICE metric, which employs scene graphs to verify the spatial relationships among the objects, described in the caption. In order to calculate the SPICE score, we need to embed the generated and ground truth captions into an intermediate scene graph representation. Via semantic parsing the captions are encoded into scene graphs. The similarity score between the generated and ground truth captions scene graphs is calculated in the form of F1 score from precision and recall. Two sets of logical tuples (that reflect semantic propositions) are created from each scene graph for generated and reference captions. The matching tuples between logical tuples for generated and reference captions divided by the total number of logical tuples in generated caption set is considered as precision and the number of matching tuples divided by total number of logical tuples in reference caption set is considered as recall. Finally the F1 score (SPICE) is calculated via multiplying precision by recall by two divided by precision added to recall.

4 Discussion

4.1 Comparison of attentive methods

In this paper, we created categories for the attentive deep learning models used for image captioning. Using these categories, we navigated through important state-of-the-art models used for image caption generation. The comparison of performance of the methods categorized and reviewed for our survey is shown in Tables 4.1. The results reported in this table correspond to experiments performed on the MS-COCO [67] dataset using Karpathy’s test split [47]. In this table, the first column describes the reference for work explained in previous section. The second column explains the types of attention used in encoders and decoders. The third column shows the kind of encoders and decoders. The results for experiments under
CIDER and SPICE metrics are available in the fourth column and fifth column respectively. The methods are first separated based on the type of attention used in decoders and second, they are separated based on their performance under CIDER score.

### Table 1 Comparison of performance among methods discussed in Section 3.2

| Reference                  | BU/SA | BU+MH/MH | OD+TR/TR | CIDER Score | SPICE Score |
|----------------------------|-------|----------|----------|-------------|-------------|
| Yao et al 2020 [12]        | BU/SA | BU+MH/MH | OD+TR/TR | 132.8       | 32.2        |
| Li et al 2019 [18]         | BU+MH/MH | OD+TR/TR | 131.5     | 32.2        | 39.7        | 20.5       |
| Guo et al 2020 [19]        | BU+MH/MH | OD+TR/TR | 131.4     | 32.0        | 39.3        | 20.2       |
| Cornia et al 2020 [24]     | BU+MH/MH | OD+TR/TR | 131.2     | 22.6        | 39.1        | 20.2       |
| Yu et al 2019 [29]         | BU+MH/MH | OD+TR/TR | 130.9     | -           | -           | 20.1       |
| Huang et al 2019 [35]      | BU+MH/MH | OD+TR/TR | 129.8     | 22.4        | 38.9        | 20.2       |
| Liu et al 2019 [38]        | BU+MH/MH | OD+TR/TR | 129.3     | 22.6        | 39.6        | 20.9       |
| Herdade et al 2019 [40]    | BU+MH/MH | OD+TR/TR | 128.3     | 22.6        | 38.6        | 20.7       |
| Li et al 2019 [41]         | BU+MH/MH | OD+TR/TR | 127.6     | 22.6        | 39.9        | 20.9       |
| Pan et al 2020 [42]        | BU+MH/MH | OD+TR/TR | 127.0     | 22.1        | 38.2        | 20.2       |
| Huang et al 2020 [42]      | BU+MH/MH | OD+TR/TR | 119.8     | 21.3        | 37.2        | -          |
| Li et al 2020 [43]         | BU+MH/MH | OD+TR/TR | 119.3     | 21.6        | 37.8        | 20.4       |
| Yu et al 2019 [44]         | BU+MH/MH | OD+TR/TR | 117.1     | -           | 37.1        | 20.1       |
| Liu et al 2019 [45]        | BU+MH/MH | OD+TR/TR | 118.2     | 21.2        | 37.9        | 20.3       |
| Herdade et al 2019 [46]    | BU+MH/MH | OD+TR/TR | 115.4     | 21.2        | 35.5        | 20.0       |
| Yao et al 2019 [48]        | BU/SA  | OD+GCN/LSTM | 130.6 | 22.3 | 39.1 | 20.9 |
| Wang et al 2020 [53]       | BU/SA  | OD+GCN/LSTM | 129.1 | 22.4 | 38.5 | 20.7 |
| Sammani et al 2020 [53]    | BU/SA  | OD/LSTM | 128.9 | 22.6 | 39.1 |        |
| Yao et al 2018 [54]        | BU/SA  | OD+GCN/LSTM | 128.7 | 22.1 | 38.3 | 26.6 |
| Huang et al 2018 [55]      | BU/SA  | OD/LSTM | 128.6 | 22.2 | 38.7 | 26.6 |
| Yang et al 2018 [56]       | BU/SA  | OD+GCN/LSTM | 127.9 | 22.0 | 38.9 | 26.4 |
| Yang et al 2019 [57]       | BU+MH | OD+GCN/LSTM | 127.8 | 22.1 | 38.4 | 26.4 |
| Qin et al 2019 [58]        | BU+MH | OD+GCN/LSTM | 127.6 | 22.0 | 38.3 | -      |
| Zhou et al 2020 [59]       | BU/SA  | OD/LSTM | 126.1 | 22.2 | 38.0 | 26.5 |
| Guo et al 2019 [60]        | BU/SA  | OD/LSTM | 125.6 | 22.3 | 37.5 | 26.5 |
| Wang et al 2019 [62]       | BU/SA  | OD/LSTM | 121.7 | 21.5 | 37.6 | 27.8 |
| Yao et al 2019 [63]        | BU/SA  | OD+GCN/LSTM | 120.3 | 21.4 | 38.0 | 26.0 |
| Li & Jiang 2018 [64]       | BU/SA  | OD+GCN/LSTM | 120.2 | 21.4 | 36.3 | 27.6 |
| Anderson et al 2018 [65]   | BU/SA  | OD/LSTM | 120.1 | 21.4 | 36.3 | 27.7 |
| Sammani et al 2018 [66]    | BU/SA  | OD/LSTM | 120.0 | 21.3 | 38.0 | -      |
| Huang et al 2018 [67]      | BU/SA  | OD+GCN/LSTM | 117.2 | 21.2 | 37.0 | 26.0 |
| Yao et al 2018 [68]        | BU/SA  | OD+GCN/LSTM | 117.1 | 21.1 | 37.1 | 26.1 |
| Wang et al 2020 [69]       | BU+MH | OD+GCN/LSTM | 116.9 | 21.3 | 36.6 | 28.0 |
| Yang et al 2019 [70]       | BU+MH | OD+GCN/LSTM | 116.6 | 20.8 | 37.1 | 27.9 |
| Qin et al 2019 [71]        | BU+MH | OD+GCN/LSTM | 116.4 | 21.2 | 37.4 | 28.1 |
| Ke et al 2019 [72]         | BU+MH | OD+GCN/LSTM | 115.3 | 21.3 | 36.8 | 27.2 |
| Wang et al 2017 [73]       | BU+MH | OD+GCN/LSTM | 114.8 | 20.6 | 36.2 | 27.5 |
| Anderson et al 2017 [74]   | BU+MH | OD+GCN/LSTM | 113.5 | 20.3 | 36.2 | 27.0 |
| Chen et al 2018 [75]       | BU/SA  | COD/LSTM | 112.2 | -     | 35.4 | 20.5 |
| Yu et al 2019 [76]         | BU/SA  | COD/LSTM | 110.7 | 20.3 | 35.5 | 27.4 |
| Li & Jiang 2017 [77]       | BU/SA  | COD+GCN/LSTM | 110.3 | 19.8 | 33.8 | 26.2 |
| Wang et al 2018 [78]       | BU/SA  | COD+GCN/LSTM | 108.6 | 20.3 | 34.5 | 26.8 |
| Lu et al 2018 [79]         | BU/SA  | COD+GCN/LSTM | 107.3 | 20.3 | 34.7 | 27.1 |

The results reported for CIDER and SPICE metrics are borrowed from the original published literature, based on experiments performed using cross-entropy loss. A self-critical loss was proposed by Renjie et al. [52] to perform reinforcement learning and optimization on the CIDER score directly. While a few of the recently published literature reviewed in previous section report results using only one of these loss functions, the majority report results using both loss functions. Therefore, we show the results from experiments that use both loss functions. We also ensure that ResNet101 or Faster-RCNN [52] with ResNet101 [35] are commonly
used for feature extraction among all compared methods to ensure fair comparison. Among all methods, in recurrent fusion network introduced by Jiang et al. \cite{45} the network utilizes multiple different CNN networks for feature extraction. Thus, the results of experiments via this model are not directly comparable with the results of other methods enumerated in Table 4.1.

The comparison of methods using automatic metrics such as CIDER and SPICE provides us with insight about the quality of the generated captions in regards with visual features, as well as insight regarding the effectiveness of different attention mechanisms employed by these methods.

For conciseness, in Table 4.1 we show the performance of all the methods reviewed in Section 3.2 in terms of CIDER and SPICE scores. Although it is important to investigate results under other metrics, usually achieving higher scores under CIDER and SPICE metrics leads to higher scores under neural machine translation metrics such as BLEU, METEOR and ROUGE. We also categorize different types of soft and multi-head attention mechanisms used in the methods discussed in Section 3.2 under soft attention (SA) and multi-head attention (MH). The reason is we want to discover the effectiveness of employing variants of multi-head attention as opposed to variants of soft attention.

In Section 3.2, we discussed the methods compared in Table 4.1 and categorized them based on the way they employ attention mechanisms in their encoders. Here we present all the methods reviewed in Section 3.2 based on the way they employ attention to create the attentive decoder. We compare the methods based on performance using the scores originally reported in the published literature. By looking at Table 4.1 we realize that bottom-up attention with multi-head attention encoders with multi-head attention decoders perform better than models that employ variants of soft attention with LSTMs as decoder alongside bottom-up attention encoder.

Another noteworthy attentive deep model used for image captioning offered by Cornia et al. \cite{17} employs the idea of controllability. By creating different combinations for the order of the same detection set containing region proposals or creating different detection sets with different objects, they create different control signals that can generate different captions. The best control signal generates the caption with the highest CIDER score. This mechanism leads to highly competitive results on the MSCOCO dataset, that are not comparable with the results gathered from experiments with other attentive models for image captioning that do not employ controllability.

Chen et al. \cite{11} improve the idea of controllability used in deep neural networks for image captioning by creating fine-grained control signals that are selected based on the information gathered from scene graphs. We did not bring the results from experiments that employ controllability into the table for comparison; the reason is that the results from these experiments are not directly comparable with the results we have enumerated in Table 4.1.

We consider controllability as one the most important new concepts that can be used for boosting the quality of generated captions. At the same time, recent work suggests that multi-head attention that employs scaled-dot attention, is more effective than soft attention. Therefore, it makes sense to investigate the ways to create controllable and grounded captions using multi-head attention and Transformer-based models.
There are also other state-of-the-art deep image captioning models that are trained in semi-supervised fashion without employing attention mechanisms. For instance, the dual generative adversarial network for image captioning by Liu et al. [69] does not employ attention mechanisms and instead relies on generative adversarial networks [92].

4.2 Discussion of attentive methods

Visual soft and hard attention [102] showed better performance in comparison with earlier methods that did not benefit from application of attention mechanism for image captioning [96, 48, 47]. In comparison with bottom-up attention that employs object level features, the downside of visual soft and hard attention is that they apply attention on visual features from the whole image rather than specific regions in the image. The soft attention was used over visual features from the whole image in most of the methods explained in Section 3.1.

Inspired by methods that applied attention on visual features towards object level features, such as SCA-CNN [10] and Areas of Attention [79], bottom-up attention [3] employs an object detector with a CNN backbone that extract the visual spatial features from specific regions in the image. Bottom-up attention improved the visual attention; however the attention was not utilized over semantic relationships among the detected regions in the image. Bottom-up attention was used along various types of soft attention applied to visual bottom-up features with other sources of information as explained in Section 3.2.2.

Instead of utilizing soft attention over visual features, semantic attention [111] leverages soft attention on attributes discovered from the image using external resources. Although the semantic attention achieved to better results in comparison with visual soft and hard attention, external resources should be used for discovering attributes in the image, which leads to increased model complexity. The semantic attention became a source of inspiration for models that employ GCNs (Section 3.2.3), which explore the spatial and semantic relationships between the regions of interest in the image.

Self-attention (scaled-dot attention) is a building block of multi-head attention. By applying self-attention on bottom-up attention features in the encoder and utilizing self-attention on the ground truth caption sequence while training, the model learns the semantic relationships among objects with reference to the semantic relationships in the ground truth caption. This is mainly the reason why the methods explained in Section 3.2.4, which use multi-head attention with bottom-up attention perform better than the methods explained in Section 3.2.3, which employ GCNs with bottom-up attention features.

Limitations of all state-of-the-art methods explained in Section 3.2 and the gaps among these methods are as the following. The fact that bottom-up attention performs visual attention at object level improves the performance of all methods that employ this method, however a key question remains whether in some wild scenarios the model needs to attend to regions in the image that do not contain any objects and rather contain natural or wild elements that the object detector has not been trained to detect (such as mountain, trees, skies and etcetera).

Regarding the self-attention in multi-head attention, because in the encoder of Transformer model the self-attention mechanism calculates similarity scores
between all elements of a sequence such as the set of bottom-up features from different regions in the image, therefore the question remains if performing masking similar to how it is done in the decoder part of the Transformer model would benefit the model to learn more important relationships among detected regions in the image rather than calculating the similarity scores between all regions.

Although recently researchers have explored various methods for enhancing the multi-head attention and self-attention for image captioning as explained in Section 3.2.4, an interesting question remains whether another attention component could be used rather than original self-attention which could potentially leverage the bottom-up features or caption sequence in conjunction with bottom-up features better for caption generation. The use of object detectors for extracting bottom-up features poses the risk of not being able to attend to regions that are relevant to captions in domains that the object detector has no knowledge about (has not been trained on). Therefore, in wild scenarios more knowledge from various domains might be required, which can be provided via object detectors trained on more specific tasks.

5 Conclusions

We have performed a survey of state-of-the-art attentive deep learning models used for image captioning. Comparison among the models reveals that Transformer-based models are leading the way with highest scores for the image captioning metrics. Other methods such as using bottom-up attention with soft-attention with LSTMs still work reasonably well and compete with multi-head attention and Transformer-based models. Using Transformer-based models employing variants of multi-head attention with bottom-up attention results in better performance. Investigating ways to improve the Transformers or using them in innovative ways seems to be the right path for further research related to neural attention mechanisms for image caption generation.

Image captioning has become a major translation task in vision-language, combining the principles of computer vision and neural machine translation. In the future, we are likely to witness widespread use of attention mechanisms in neural image captioning systems in various tasks. Medical image captioning is an instance of a task which may be beneficial to the medical community. Image captioning performed on mobile devices may become useful to visually impaired, especially when communicated verbally. Bringing visual intelligence for robots and enhancing visual recommendation systems and visual assistant systems are among other applications of neural image captioning. Attention mechanisms have shown the ability to map important parts of multi-modal information for use in downstream tasks such as image captioning. Improving visual attention mechanisms (such as bottom-up, SCA-CNN, Areas-of-Attention) and multi-modal (soft) attention mechanisms as well as multi-head attention and self-attention for image captioning remains an interesting challenge for the research community.
Conflicts of interest/Competing interests

The authors declare that they have no conflict of interest or competing interest in this work. N/A

References

1. Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics, July 6-12, 2002, Philadelphia, PA, USA. ACL (2002)
2. Anderson, P., Fernando, B., Johnson, M., Gould, S.: Spice: Semantic propositional image caption evaluation. In: ECCV (2016)
3. Anderson, P., He, X., Buehler, C., Teney, D., Johnson, M., Gould, S., Zhang, L.: Bottom-up and top-down attention for image captioning and visual question answering. In: CVPR (2018)
4. Aneja, J., Deshpande, A., Schwing, A.G.: Convolutional image captioning. In: 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 5561–5570 (2018). DOI 10.1109/CVPR.2018.00583
5. Bahdanau, D., Cho, K., Bengio, Y.: Neural machine translation by jointly learning to align and translate. In: 3rd International Conference on Learning Representations, ICLR 2015 (2015)
6. Bai, S., An, S.: A survey on automatic image caption generation. Neurocomputing 311, 291 – 304 (2018). DOI https://doi.org/10.1016/j.neucom.2018.05.080. URL http://www.sciencedirect.com/science/article/pii/S0925231218306659
7. Bengio, Y., LeCun, Y., Henderson, D.: Globally trained handwritten word recognizer using spatial representation, convolutional neural networks, and hidden markov models. In: Advances in Neural Information Processing Systems 6, pp. 937–944. Morgan-Kaufmann (1994)
8. Bruna, J., Zaremba, W., Szlam, A., LeCun, Y.: Spectral networks and locally connected networks on graphs. In: Y. Bengio, Y. LeCun (eds.) 2nd International Conference on Learning Representations, ICLR 2014, Banff, AB, Canada, April 14-16, 2014, Conference Track Proceedings (2014). URL http://arxiv.org/abs/1312.6203
9. Chen, C., Mu, S., Xiao, W., Ye, Z., Wu, L., Ju, Q.: Improving image captioning with conditional generative adversarial nets. Proceedings of the AAAI Conference on Artificial Intelligence 33(01), 8142–8150 (2019). DOI 10.1609/aaai.v33i01.33018142
10. Chen, L., Zhang, H., Xiao, J., Nie, L., Shao, J., Liu, W., Chua, T.S.: Sca-cnn: Spatial and channel-wise attention in convolutional networks for image captioning. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2017)
11. Chen, S., Jin, Q., Wang, P., Wu, Q.: Say as you wish: Fine-grained control of image caption generation with abstract scene graphs. In: IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) (2020)
12. Chen, S., Zhao, Q.: Boosted attention: Leveraging human attention for image captioning. In: The European Conference on Computer Vision (ECCV) (2018)
13. Cho, K., Courville, A., Bengio, Y.: Describing multimedia content using attention-based encoder-decoder networks. IEEE Transactions on Multimedia 17(11), 1875–1886 (2015). DOI 10.1109/TMM.2015.2477044
14. Cho, K., Courville, A.C., Bengio, Y.: Describing multimedia content using attention-based encoder-decoder networks. IEEE Trans. Multimedia 17(11), 1875–1886 (2015)
15. Cho, K., van Merrienboer, B., Bahdanau, D., Bengio, Y.: On the properties of neural machine translation: Encoder–decoder approaches. In: Proceedings of SSST-8, Eighth Workshop on Syntax, Semantics and Structure in Statistical Translation, pp. 103–111. Association for Computational Linguistics, Doha, Qatar (2014). DOI 10.3115/v1/W14-4012. URL https://www.aclweb.org/anthology/W14-4012
16. Cho, K., van Merrienboer, B., Gulcehre, C., Bahdanau, D., Bougares, F., Schwenk, H., Bengio, Y.: Learning phrase representations using RNN encoder–decoder for statistical machine translation. In: Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP), pp. 1724–1734. ACL, Doha, Qatar (2014). DOI 10.3115/v1/D14-1179
17. Cornia, M., Baraldi, L., Cucchiara, R.: Show, control and tell: A framework for generating controllable and grounded captions. In: The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2019)
18. Cornia, M., Stefanini, M., Baraldi, L., Cucchiara, R.: Meshed-memory transformer for image captioning. In: IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) (2020)
19. Dai, B., Fidler, S., Urtasun, R., Lin, D.: Towards diverse and natural image descriptions via a conditional gan. In: Proceedings of the IEEE International Conference on Computer Vision (ICCV) (2017)
20. Defferrard, M., Bresson, X., Vandergheynst, P.: Convolutional neural networks on graphs with fast localized spectral filtering. In: Advances in Neural Information Processing Systems, vol. 29, pp. 3844–3852 (2016)
21. Deng, J., Dong, W., Socher, R., Li, L.J., Li, K., Fei-Fei, L.: ImageNet: A Large-Scale Hierarchical Image Database. In: CVPR09 (2009)
22. Desmet, H., Schneider, W.X.: Saccade target selection and object recognition: Evidence for a common attentional mechanism. Vision Research 36(12), 1827 – 1837 (1996). DOI https://doi.org/10.1016/0042-6989(95)00294-4
23. Donahue, J., Anne Hendricks, L., Guadarrama, S., Rohrbach, M., Venugopalan, S., Saenko, K., Darrell, T.: Long-term recurrent convolutional networks for visual recognition and description. In: The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2015)
24. Fang, H., Gupta, S., Iandola, F., Srivastava, R.K., Deng, L., Dollar, P., Gao, J., He, X., Mitchell, M., Platt, J.C., Lawrence Zitnick, C., Zweig, G.: From captions to visual concepts and back. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2015)
25. Farhadi, A., Hejrati, M., Sadeghi, M.A., Young, P., Rashtchian, C., Hockenmaier, J., Forsyth, D.: Every picture tells a story: Generating sentences from images. In: Computer Vision – ECCV 2010, pp. 15–29. Springer Berlin Heidelberg, Berlin, Heidelberg (2010)
26. Feng, Y., Ma, L., Liu, W., Luo, J.: Unsupervised image captioning. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2019)
27. Fu, K., Jin, J., Cui, R., Sha, F., Zhang, C.: Aligning where to see and what to tell: Image captioning with region-based attention and scene-specific contexts. IEEE Transactions on Pattern Analysis and Machine Intelligence 39(12), 2321–2334 (2017). DOI 10.1109/TPAMI.2016.2642953
28. Gao, L., Fan, K., Song, J., Liu, X., Xu, X., Shen, H.T.: Deliberate attention networks for image captioning. Proceedings of the AAAI Conference on Artificial Intelligence 33(01), 8320–8327 (2019). DOI 10.1609/aaai.v33i01.33018320
29. Girshick, R.: Fast r-cnn. In: The IEEE International Conference on Computer Vision (ICCV) (2015)
30. Girshick, R., Donahue, J., Darrell, T., Malik, J.: Rich feature hierarchies for accurate object detection and semantic segmentation. In: 2014 IEEE Conference on Computer Vision and Pattern Recognition, pp. 580–587 (2014). DOI 10.1109/CVPR.2014.81
31. Gong, Y., Wang, L., Hodosh, M., Hockenmaier, J.C., Lazebnik, S.: Improving image-sentiment embeddings using large weakly annotated photo collections. In: Computer Vision, ECCV 2014 - 13th European Conference, Proceedings, no. PART 4 in Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), pp. 529–545. Springer-Verlag (2014). DOI 10.1007/978-3-319-10593-2_35
32. Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., Bengio, Y.: Generative adversarial nets. In: Z. Ghahramani, M. Welling, C. Cortes, N.D. Lawrence, K.Q. Weinberger (eds.) Advances in Neural Information Processing Systems 27, pp. 2672–2680. Curran Associates, Inc. (2014). URL http://papers.nips.cc/paper/5423-generative-adversarial-nets.pdf
33. Guo, L., Liu, J., Zhu, X., Yao, P., Lu, S., Lu, H.: Normalized and geometry-aware self-attention network for image captioning. In: IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) (2020)
34. He, K., Gkioxari, G., Dollar, P., Girshick, R.: Mask r-cnn. In: The IEEE International Conference on Computer Vision (ICCV) (2017)
35. He, K., Zhang, X., Ren, S., Sun, J.: Deep residual learning for image recognition. In: The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2016)
36. Herdade, S., Kappeler, A., Boakye, K., Soares, J.: Image captioning: Transforming objects into words. In: Advances in Neural Information Processing Systems 32, pp. 11135–11145 (2019)
37. Hochreiter, S., Schmidhuber, J.: Long short-term memory. Neural Comput. 9(8), 1735–1780 (1997). DOI 10.1162/neco.1997.9.8.1735
38. Hodosh, M., Young, P., Hockenmaier, J.C.: Framing image description as a ranking task: Data, models and evaluation metrics. In: IJCAI 2015 - Proceedings of the 24th International Joint Conference on Artificial Intelligence, IJCAI International Joint Conference on Artificial Intelligence, pp. 4188–4192. International Joint Conferences on Artificial Intelligence (2015)
39. Hossain, M.Z., Sohel, F., Shiratuddin, M.F., Laga, H.: A comprehensive survey of deep learning for image captioning. ACM Comput. Surv. 51(6), 118:1–118:36 (2019). DOI 10.1145/3295748
40. Huang, L., Wang, W., Chen, J., Wei, X.Y.: Attention on attention for image captioning. In: The IEEE International Conference on Computer Vision (ICCV) (2019)
41. Huang, L., Wang, W., Xia, Y., Chen, J.: Adaptively aligned image captioning via adaptive attention time. In: Advances in Neural Information Processing Systems 32, pp. 8940–8949 (2019)
42. Ioffe, S., Szegedy, C.: Batch normalization: Accelerating deep network training by reducing internal covariate shift. In: Proceedings of the 32Nd International Conference on International Conference on Machine Learning - Volume 37, ICML'15, pp. 448–456. JMLR.org (2015)
43. Jaderberg, M., Simonyan, K., Zisserman, A., kavukcuoglu, k.: Spatial transformer networks. In: C. Cortes, N. Lawrence, D. Lee, M. Sugiyama, R. Garnett (eds.) Advances in Neural Information Processing Systems, vol. 28 (2015)
44. Jia, X., Gavves, E., Fernando, B., Tuytelaars, T.: Guiding the long-short term memory model for image caption generation. In: The IEEE International Conference on Computer Vision (ICCV) (2015)
45. Jiang, W., Ma, L., Jiang, Y.G., Liu, W., Zhang, T.: Recurrent fusion network for image captioning. In: Computer Vision – ECCV 2018, pp. 510–526 (2018)
46. Kalchbrenner, N., Blunsom, P.: Recurrent continuous translation models. In: Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing, pp. 1700–1709. ACL, Seattle, Washington, USA (2013). URL https://www.aclweb.org/anthology/D13-1176
47. Karpathy, A., Fei-Fei, L.: Deep visual-semantic alignments for generating image descriptions. In: The IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 3128–3137. IEEE Computer Society (2015)
48. Karpathy, A., Joulin, A., Pei-Fei, L.F.: Deep fragment embeddings for bidirectional image sentence mapping. In: Advances in Neural Information Processing Systems 27, pp. 1889–1897. Curran Associates, Inc. (2014)
49. Ke, L., Pei, W., Li, R., Shen, X., Tai, Y.W.: Reflective decoding network for image captioning. In: The IEEE International Conference on Computer Vision (ICCV) (2019)
50. Kingma, D.P., Ba, J.: Adam: A method for stochastic optimization. International Conference on Learning Representations (ICLR) (2015)
51. Kiros, R., Salakhutdinov, R., Zemel, R.: Multimodal neural language models. In: Proceedings of the 31st International Conference on Machine Learning, Proceedings of Machine Learning Research, vol. 32, pp. 595–603. PMLR (2014)
52. Kiros, R., Salakhutdinov, R.R., Zemel, R.S.: Unifying visual-semantic embeddings with multimodal neural language models. CoRR abs/1411.2539 (2014)
53. Koch, C., Ullman, S.: Shifts in Selective Visual Attention: Towards the Underlying Neural Circuitry, pp. 115–141. Springer Netherlands, Dordrecht (1987). DOI 10.1007/978-94-009-3835-5_5
54. Krizhevsky, A., Sutskever, I., Hinton, G.E.: Imagenet classification with deep convolutional neural networks. In: Advances in Neural Information Processing Systems 25, pp. 1097–1105. Curran Associates, Inc. (2012)
55. Kulkarni, G., Premraj, V., Ordonez, V., Dhar, S., Li, S., Choi, Y., Berg, A.C., Berg, T.L.: Babytalk: Understanding and generating simple image descriptions. IEEE Transactions on Pattern Analysis and Machine Intelligence 35(12), 2891–2903 (2013). DOI 10.1109/TPAMI.2012.162
56. Laina, I., Rupprecht, C., Navah, N.: Towards unsupervised image captioning with shared multimodal embeddings. In: The IEEE International Conference on Computer Vision (ICCV) (2019)
57. Lavie, A., Denkowski, M.J.: The meteor metric for automatic evaluation of machine translation. Machine Translation 23(2-3), 105–115 (2009). DOI 10.1007/s10590-009-0959-4
58. LeCun, Y., Boser, B., Denker, J.S., Henderson, D., Howard, R.E., Hubbard, W., Jackel, L.D.: Backpropagation applied to handwritten zip code recognition. Neural Computation 1(4), 541–551 (1989). DOI 10.1162/neco.1989.1.4.541
59. LeCun, Y., Bottou, L., Bengio, Y., Haffner, P.: Gradient-based learning applied to document recognition. Proceedings of the IEEE 86(11), 2278-2324 (1998)
60. Li, G., Zhu, L., Liu, P., Yang, Y.: Entangled transformer for image captioning. In: The IEEE International Conference on Computer Vision (ICCV) (2019)
61. Li, J., Yao, P., Guo, L., Zhang, W.: Boosted transformer for image captioning. Applied Sciences 9(16) (2019). DOI 10.3390/app9163260
62. Li, L., Tang, S., Deng, L., Zhang, Y., Tian, Q.: Image caption with global-local attention. Proceedings of the AAAI Conference on Artificial Intelligence 31(1) (2017). URL https://ojs.aaai.org/index.php/AAAI/article/view/11236
63. Li, S., Kulkarni, G., Berg, T.L.; Berg, A.C.; Choi, Y.: Composing simple image descriptions using web-scale n-grams. In: Proceedings of the Fifteenth Conference on Computational Natural Language Learning, CoNLL ‘11, pp. 220–228. Association for Computational Linguistics, Stroudsburg, PA, USA (2011)
64. Li, S., Tao, Z., Li, K., Fu, Y.: Visual to text: Survey of image and video captioning. IEEE Transactions on Emerging Topics in Computational Intelligence 3(4), 297–312 (2019)
65. Li, X., Jiang, S.: Know more say less: Image captioning based on scene graphs. IEEE Transactions on Multimedia 21(8), 2117–2130 (2019). DOI 10.1109/TMM.2019.286516
66. Lin, C.Y.: ROUGE: A package for automatic evaluation of summaries. In: Text Summarization Branches Out, pp. 74–81. Association for Computational Linguistics, Barcelona, Spain (2004). URL https://www.aclweb.org/anthology/W04-1013
67. Lin, T.Y., Maire, M., Belongie, S.; Hays, J.; Perona, P.; Ramanan, D.; Dollar, P.; Zitnick, C.L.: Microsoft coco: Common objects in context. In: Computer Vision – ECCV 2014, pp. 740–755. Springer International Publishing, Cham (2014)
68. Liu, F., Ren, X., Liu, Y., Lei, K., Sun, X.: Exploring and distilling cross-modal information for image captioning. In: Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence, IJCAI-19, pp. 5095–5101 (2019). DOI 10.24963/ijcai.2019/708
69. Liu, J., Wang, K., Xu, C., Zhao, Z., Xu, R., Shen, Y., Yang, M.: Interactive dual generative adversarial networks for image captioning. In: The Thirty-Fourth AAAI Conference on Artificial Intelligence, AAAI 2020, pp. 11588–11595 (2020). DOI https://doi.org/10.1609/aaai.v34i07.6826
70. Liu, X., Xu, Q., Wang, N.: A survey on deep neural network-based image captioning. The Visual Computer 35(3), 445–470 (2019). DOI 10.1007/s00371-018-1566-y
71. Long, J., Shelhamer, E., Darrell, T.: Fully convolutional networks for semantic segmentation. In: The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2015)
72. Lu, J., Xiong, C., Parikh, D., Socher, R.: Knowing when to look: Adaptive attention via a visual sentinel for image captioning. 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR) pp. 3242–3250 (2017)
73. Lu, J., Yang, J., Batra, D., Parikh, D.: Neural baby talk. In: CVPR (2018)
74. Mikolov, T., Sutskever, I., Chen, K., Corrado, G., Dean, J.: Distributed representations of words and phrases and their compositionality. In: Proceedings of the 26th International Conference on Neural Information Processing Systems - Volume 2, NIPS’13, pp. 3111–3119. Curran Associates Inc., USA (2013)
75. Mun, J., Cho, M., Han, B.: Text-guided attention model for image captioning. In: AAAI Conference on Artificial Intelligence (2017)
76. Ordonez, V., Kulkarni, G., Berg, T.L.: Im2Text: Describing images using 1 million captioned photographs. In: Advances in Neural Information Processing Systems 24, pp. 1143–1151. Curran Associates, Inc. (2011)
77. Pan, Y., Yao, T., Li, Y., Mei, T.: X-linear attention networks for image captioning. In: IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) (2020)
78. Pavlopoulos, J., Kougia, V., Androutsopoulos, I.: A survey on biomedical image captioning. In: Proceedings of the Second Workshop on Shortcomings in Vision and Language, pp. 26–36. Association for Computational Linguistics, Minneapolis, Minnesota (2019). DOI 10.18653/v1/W19-1803
79. Pedersoli, M., Lucas, T., Schmid, C., Verbeek, J.: Areas of attention for image captioning. In: Proceedings of the IEEE International Conference on Computer Vision (ICCV) (2017)

80. Pennington, J., Socher, R., Manning, C.D.: Glove: Global vectors for word representation. In: Empirical Methods in Natural Language Processing (EMNLP), pp. 1532–1543 (2014)

81. Qin, Y., Du, J., Zhang, Y., Lu, H.: Look back and predict forward in image captioning. In: The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2019)

82. Ren, S., He, K., Girshick, R., Sun, J.: Faster r-cnn: Towards real-time object detection with region proposal networks. In: Advances in Neural Information Processing Systems 28, pp. 91–99. Curran Associates, Inc. (2015)

83. Rennie, S.J., Marcheret, E., Mroueh, Y., Ross, J., Goel, V.: Self-critical sequence training for image captioning. In: The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2017)

84. Sammani, F., Melas-Kyriazi, L.: Show, edit and tell: A framework for editing image captions. In: IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) (2020)

85. Sharma, H., Agrahari, M., Singh, S.K., Firoj, M., Mishra, R.K.: Image captioning: A comprehensive survey. In: 2020 International Conference on Power Electronics IoT Applications in Renewable Energy and its Control (PARC), pp. 325–328 (2020)

86. Shrestha, K., Image captioning via personality. In: The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2019)

87. Simonyan, K., Zisserman, A.: Very deep convolutional networks for large-scale image recognition. CoRR abs/1409.1556 (2014)

88. Sun, C., Gan, C., Nevatia, R.: Automatic concept discovery from parallel text and visual corpora. In: The IEEE International Conference on Computer Vision (ICCV) (2015)

89. Sutskever, I., Vinyals, O., Le, Q.V.: Sequence to sequence learning with neural networks. In: Advances in Neural Information Processing Systems 27, pp. 3104–3112. Curran Associates, Inc. (2014)

90. Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V., Rabinovich, A.: Going deeper with convolutions. In: The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2015)

91. Tieleman, T., Hinton, G.: Lecture 6.5—RmsProp: Divide the gradient by a running average of its recent magnitude. COURSERA: Neural Networks for Machine Learning (2012)

92. Uijlings, J.R., Sande, K.E., Gevers, T., Smeulders, A.W.: Selective search for object recognition. Int. J. Comput. Vision 104(2), 154–171 (2013). DOI 10.1007/s11263-013-0620-5

93. Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A.N., Kaiser, Ł., Polosukhin, I.: Attention is all you need. In: Advances in Neural Information Processing Systems 30, pp. 5998–6008. Curran Associates, Inc. (2017)

94. Vedantam, R., Lawrence Zitnick, C., Parikh, D.: Cider: Consensus-based image description evaluation. In: The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2015)

95. Vinyals, O., Toshev, A., Bengio, S., Erhan, D.: Show and tell: A neural image caption generator. In: The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2015)

96. Wang, D., Beck, D., Cohn, T.: On the role of scene graphs in image captioning. In: Proceedings of the Beyond Vision and Language, pp. 29–34. Association for Computational Linguistics (2019). DOI 10.18653/v1/D19-6405

97. Wang, L., Bai, Z., Zhang, Y., Lu, H.: Show, recall, and tell: A neural image caption generator. Proceedings of the AAAI Conference on Artificial Intelligence, AAAI 2020, pp. 12176–12183 (2020). DOI https://doi.org/10.1609/aaai.v34i07.6898

98. Wang, W., Chen, Z., Hu, H.: Hierarchical attention network for image captioning. Proceedings of the AAAI Conference on Artificial Intelligence 33, 8957–8964 (2019). DOI 10.1609/aaai.v33i01.33018957

99. Wei, Y., Wang, L., Cao, H., Shao, M., Wu, C.: Multi-attention generative adversarial network for image captioning. Neurocomputing 387, 91–99 (2020). DOI https://doi.org/10.1016/j.neucom.2019.12.073

100. Xie, S., Girshick, R., Dollar, P., Tu, Z., He, K.: Aggregated residual transformations for deep neural networks. In: The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2017)
102. Xu, K., Ba, J., Kiros, R., Cho, K., Courville, A., Salakhudinov, R., Zemel, R., Bengio, Y.: Show, attend and tell: Neural image caption generation with visual attention. In: Proceedings of the 32nd International Conference on Machine Learning, Proceedings of Machine Learning Research, vol. 37, pp. 2048–2057. PMLR (2015)

103. Xu Huijuan and Saenko, K.: Ask, attend and answer: Exploring question-guided spatial attention for visual question answering. In: Computer Vision – ECCV 2016, pp. 451–466. Springer International Publishing, Cham (2016)

104. Yang, X., Tang, K., Zhang, H., Cai, J.: Auto-encoding scene graphs for image captioning. In: The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2019)

105. Yang, X., Zhang, H., Cai, J.: Learning to collocate neural modules for image captioning. In: The IEEE International Conference on Computer Vision (ICCV) (2019)

106. Yang, Z., He, X., Gao, J., Deng, L., Smola, A.: Stacked attention networks for image question answering. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2016)

107. Yao, T., Pan, Y., Li, Y., Mei, T.: Exploring visual relationship for image captioning. In: Computer Vision – ECCV 2018, pp. 711–727 (2018)

108. Yao, T., Pan, Y., Li, Y., Mei, T.: Hierarchy parsing for image captioning. In: The IEEE International Conference on Computer Vision (ICCV) (2019)

109. Yao, T., Pan, Y., Li, Y., Qiu, Z., Mei, T.: Boosting image captioning with attributes. In: 2017 IEEE International Conference on Computer Vision (ICCV), pp. 4904–4912 (2017). DOI 10.1109/ICCV.2017.524

110. Ye, S., Han, J., Liu, N.: Attentive linear transformation for image captioning. IEEE Transactions on Image Processing 27(11), 5514–5524 (2018). DOI 10.1109/TIP.2018.2855496

111. You, Q., Jin, H., Wang, Z., Fang, C., Luo, J.: Image captioning with semantic attention. In: The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2016)

112. Young, P., Lai, A., Hodosh, M., Hockenmaier, J.: From image descriptions to visual denotations: New similarity metrics for semantic inference over event descriptions. TACL 2, 67–78 (2014)

113. Yu, J., Li, J., Yu, Z., Huang, Q.: Multimodal transformer with multi-view visual representation for image captioning. IEEE Transactions on Circuits and Systems for Video Technology pp. 1–1 (2019). DOI 10.1109/TCSVT.2019.2947482

114. Zhou, L., Xu, C., Koch, P., Corso, J.J.: Watch what you just said: Image captioning with text-conditional attention. In: Proceedings of the on Thematic Workshops of ACM Multimedia 2017, p. 305–313. Association for Computing Machinery, New York, NY, USA (2017). DOI 10.1145/3126686.3126717

115. Zhou, Y., Wang, M., Liu, D., Hu, Z., Zhang, H.: More grounded image captioning by distilling image-text matching model. In: IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) (2020)

116. Zhu, X., Li, L., Liu, J., Peng, H., Niu, X.: Captioning transformer with stacked attention modules. Applied Sciences 8(5) (2018). DOI 10.3390/app8050739

117. Zitnick, C.L., Dollár, P.: Edge boxes: Locating object proposals from edges. In: Computer Vision – ECCV 2014, pp. 391–405. Springer International Publishing (2014)