Deep Learning Approaches for Automated Image Captioning: A Comparative Analysis

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1. Introduction

In 2014, deep learning-based end-to-end image captioning models were brought into play for the very first time, and since then, researchers from several domains have demonstrated their deep learning capabilities by proposing various architectures. These innovative ideas tend towards the reduction in model size and parameters along with improved performance. A plethora of methods introduced deep learning models as the state-of-the-art resulting from enhancements through leveraging different properties of the spatial regions and temporal sequences. These properties suggest a wide span from spatial attention mechanisms to temporal extension. Despite these state-of-the-art models, a comprehensive evaluation from a performance perspective has not been presented.

Image captioning is the process of creating a textual description of a given image. It combines visual recognition and natural language processing. Recently, deep learning methods have been introduced to enable the automatic generation of human-like captions. In this paper, a comprehensive survey of deep learning-based image captioning models is presented, covering the early approaches to the state-of-the-art models. A performance-centric in-depth comparative analysis of these models is presented. It encompasses a qualitative and quantitative comparison of various models in terms of spatial and temporal attention mechanisms, different encoding and decoding architectures, extensions of RNN, and the use of extra information like external language models. Finally, the findings of the comparative analysis are summarized with the associated challenges and trends of future research indicated. Moreover, methods to tackle the common issues of generated captions and a discussion on evaluation metrics are also presented, respectively.

2. Foundations of Deep Learning

2.1. Background Deep Learning (DL) has been the focus of Machine Learning communities as one of the most powerful concepts involved in the field. While the term has definitely gained popularity in recent years and there has been significant progress made, the concept is not new. The term Multi-

Layer Perceptron (MLP) has been used since the 1940s. However, if agreed upon its definition, it originated from the 1986 paper by Hinton et al. With the prior knowledge from several domains of study, as well as the extraordinary advances concerning hardware and volume of data, the DL resurgence started in the early 2010s. Many of the aforementioned concepts were made possible by several technological factors: datasets were gradually increased in size, schema models were redesigned to perform tasks on larger datasets, and thanks to massive parallelization in GPUs, the training of these models achieved incredibly fast times.

This section comprises the background for all technologies and techniques referred to in the paper: huge datasets, deep artificial neural networks, and particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). Topics include how each architecture is designed, highlights from their evolution, their most used types, and how the training process is handled.

2.1. Neural Networks

Deep learning models learn through multiple layers of learning, with the first layer interpreting the input data, and each subsequent layer selecting features from the data. Convolutional neural networks are a deep learning model that is well-suited for analyzing image data. They automatically identify features in the input images and can be fine-tuned to recognize a set of classes. A connection between the inputs and outputs of the layers is formed by the neurons, the virtual definition of which contains a simple on-off mechanism that decides whether to increase or decrease the weighted input by firing an action potential—that is imitated by sending a signal down the neuron's output. After the activation, the user can add an additional constraint to the model to help prevent overfitting, which occurs when the architecture of the model is overly complex relative to the amount of training data. In the case of typical architectures used for image-related tasks, we are primarily interested in the combination of neurons, the so-called receptive field properties of the structure, which allow the model to be applied to its specific task.

Neural networks are a family of machine learning methods that are based on the structure and function of the brain. These methods are used to assign a category to an image (image classification), describe the content of an image (image captioning), and predict the likelihood of future events occurring (sequence prediction). Modern applications of deep learning in the field of computer vision that deal with these image-related tasks perform very well, as deep learning allows more abstract representations of the input data to be learned. Deep learning attempts to model high-level abstractions in data by using multiple layers in a neural network structure. During training, a dataset is used to adjust the parameters of the deep learning model to allow it to recognize and not just see.

3. Image Understanding in Deep Learning

Deep learning models predominantly apply convolutional neural networks (CNNs) with various architectures to automate the processes involved in image understanding. These models are employed to process the input visual content to recognize the presence of individual classes, with the eventual objective of outputting a precise and accurate description of the full input content. Modern state-of-the-art systems are capable of converting the input visual content, together with the information concerning the presence of descriptive entity-level content, into a concise high-level structured written description for the image. This descriptive text typically comprises full sentence content. It is this process that defines the specific area within automated visual understanding that is commonly referred to as image captioning.

Image understanding is identified as a computer vision task for automating the processing of the content of an input image to interpret and recognize the content in the image. Specifically, developing a comprehensive understanding of each part of the input visual content in a way that the trained image labeling or labeling model is capable of providing responses between the required categories. Such responses include recognition of objects at various positions and with differing appearances, recognition of the appearance or presence of a wide range of object categories, and recognition of other visual content details such as capturing each object that serves as an entity within the image at a varying level of detail. The majority of image understanding processes are conducted utilizing deep learning models, which are recognized for their ability to function well when dealing with multimodal processing that includes vision and language.

3.1. Convolutional Neural Networks

The catalyst for the convolutional layer is to leverage the spatial locality of adjacent neurons by bulk processing the input array and reducing the computational cost. We often utilize tasks like edge detection, texture recognition, and basic object identification by sharing inherently discerning filters. These basic filters can detect generic features that have been indicated to accomplish augmentation in the training set, rather than mere decrease in the receptive field. The mentioned reason greatly contributes to the capacity of the architecture to be generalized across a broad range of image classification tasks. It also accounts for the successes of transfer learning from CNNs trained on the large-scale labeled datasets. For natural language processing, CNN-based models can effectively process raw video and break it down into frames, compress the pixels into a visual embedding, and encode a rich context using 1D temporal convolutions.

Artificial neural networks have gained notable popularity in visual recognition tasks like object detection, image segmentation, and image classification from the last decade. Especially, the deployment of deep convolutional neural networks (CNNs) performed on a GPU to feed a large-scale amount of classified and labeled images for training gave promising results. The CNNs consist of two main layers: the convolutional/feature extracting layer and the activation/pooling layer. The convolutional layer is accountable for extracting features from an image, ignoring their position. Usually, this first hidden layer is the most computationally difficult and accounts for the greatest number of parameters during the training process. Despite their lower parameters, the feature maps within the convolutional layer capture meaningful semantic information that will be utilized by higher layers of the network.

4. Natural Language Processing Basics

Most of the NLP tools are derived from the application of Information Retrieval (IR) and Data Mining techniques to process unstructured language data. The unsuitability of the most formal NLP approach to full natural language treatment led to the seeking of new NLP techniques to be applied in the diverse task demands of language. In this context, the permitted language treatment tool has been the technological frontier of the current state of the art in both NLP and AI. Data, even with different aspects in the application.

Historically, the approaches used in the majority of NLP applications are based on Goodman's definition of NLP as "an art of mapping human language data into artificial language." More specifically, NLP encompasses the set of operations for the automatic parsing, classification, and generation of complex natural language sentences, paragraphs, or texts. It is commonly focused on the automatic generation of simple language structures. The majority of NLP solutions use handcrafted knowledge together with linguistically oriented approaches, limiting the scope of results and further domain application. Developed NLP solutions are heavily oriented towards simplified grammar that does not reflect natural language features, capturing only part of the underlying meaning of the language. Even the programs that use higher complexity vary in results, perception, and knowledge underlying in the sentence's context.

4.1. Word Embeddings

To overcome this limitation, the Continuous Bag of Words (CBOW) model was created. This model analyzes a word given its context and aims to predict the probability of a word based on the words before and after it. It uses a function called "projection words" that multiplies a one-hot vector of the word context to form a low-dimensional word embedding. Another model, called Skip-gram, also

analyzes a word within a context, but in this architecture, the input is the target word, and the aim is to predict the words around it. These methods are useful in training algorithms for estimating the weights of neural network layers and calculating semantic word information as real-valued word embeddings.

Traditionally, approaches to NLP tasks treat words as discrete, sparse, one-hot, and high-dimensional vectors. However, these approaches have been seen as expensive and inefficient due to the dimensionality of the vectors being estimated based on the size of the vocabulary or corpus, resulting in some noise. Researchers have addressed this issue by using dimensionality reduction techniques in information retrieval and content-based recommendation systems. These techniques consider terms as independent events using the Bag-of-Words (BoW) model, but they fall short in representing semantic information among words and phrases.

5. Automated Image Captioning

The core of the presented study is to provide detailed comparative insights into the state-of-the-art deep learning approaches for the automated image captioning task. Prior studies have provided extensive evaluations based on descriptive comparisons, such as the Vinyals and AIDL model led by the authors, and focused on the design of individual architectures like image embeddings and characteristic models for specific datasets. In addition, prior comparisons do not include many present-day deep learning models for the image captioning task.

The idea of generating captions automatically has several applications, such as accessibility tools for the visually impaired, enabling visually relevant image retrieval from textual queries, and enriching web content for search engines that rely mainly on text for retrieval. Since the task of generating captions involves combining visual and linguistic abilities, numerous cross-disciplinary studies and joint models have been developed towards this end, including multimodal RNN for visual question answering, spatiotemporal attention on videos, and others. Fashion image generation also benefits from combining related text and images.

This article treats the task of generating a textual description for a given image as automated image captioning. Given an image, the developed system aims to output a fluent and grammatical phrase describing the image. Ironically, unlike humans, generating targeted image captions needs image understanding capabilities.

Automated image captioning involves generating a textual description of a given image, an interdisciplinary task that finds important applications in areas such as accessibility and multimedia

information retrieval. It faces several challenges compared to text-based captioning, most of which stem from the unstructured nature of images. Recent studies have shown the capability of deep learning approaches to perform image captioning by leveraging CNNs for encoding the image and RNNs or other deep neural models for generating the description. An accurate comparison of the various strategies is essential to assess their merits. To this end, we provide a detailed comparative analysis of the existing deep learning models for performing automated image captioning.

5.1. Traditional Methods vs. Deep Learning

The main reason for this is that in real life, objects cannot be consistently described by a few words. Our language evolved to be highly ambiguous, and much of our knowledge about the world is either difficult to describe in a simple, concise manner or deeply ingrained in our subconscious. People used to believe that human intelligence could be reduced to a list of rules. But as recent understanding in the fields of neuroscience, cognitive science, and the famous paradox formulated by Searle suggests, common sense intelligence is not a symbol manipulation problem. The deep learning revolution started with the construction of learning systems capable of processing sensory information in a way similar to biological systems, and quickly made it a common folklore that computer vision, natural language processing, and other high-level cognitive tasks would easily fall to the mighty power of multi-layer perceptrons.

The automated image captioning task is a good example of this. Hand-crafted approaches to solving this task involve some extent of effort in curating a database matching images with descriptive sentences. These databases are then used to fit models, which are evaluated using the loss functions defined in Equation (5) and the BLEU score. The simplest approach to solving the problem involves extracting the features of the image and sentence vector representations using an appropriate function - e.g., a bag of words, a set of keywords, an embedding matrix - and then measuring the similarity between them. More sophisticated methods use natural language processing techniques to create more powerful vector representations. These models can achieve satisfactory results in some controlled conditions, but fail in practice.

6. Deep Learning Architectures for Image Captioning

This chapter presents the existing deep learning techniques used in the automatic image captioning task, classifies the different ideas they are based on, and compares them with respect to dataset, qualitative and quantitative results, and specific architecture. We draw some practical, useful suggestions from the observations made in this chapter. We focused on the most recent approaches in the state-of-the-art and also on the most interesting solutions for our readers and practitioners who

would like to make a first dive in this crucial and captivating context. Since 2016, most of the contributions concerning deep learning architectures in the field of image captioning have usually fallen into the field of Image-to-Text models generalizing the Encoder-Decoder approaches, or have adapted or combined well-known models.

Image captioning combines the disciplines of computer vision and natural language processing. An automatic image captioning system, given an image as input, produces a textual description of that image. This permits computers to extract information from images and translate that into sentences. Despite its significance, tasks, and challenges, deep learning architectures for automated image captioning have not been reviewed yet. We, therefore, are now providing an exhaustive comparison of them in this work.

6.1. Recurrent Neural Networks

Recurrent neural networks (RNN) are a class of neural models that perform parallel distributed processing. Different from feed forward networks, the RNNs have internal state which is updated at each time step. RNNs are also known as connectionist temporal classification or sequential output classification, so they are preferred for sequence labeling, machine translation, ASR, and image captioning tasks where time precedence is crucial in estimating the model. The basic idea of using RNNs for image captioning is to regard images as sequences of regions. In contrast to CNN and other encoder-decoder models like Sutskever et al. (2014), Vinyals et al. (2015), RNNs are end-to-end models for image captioning trained using back propagation, starting with the visual features of image and assuming no external supervision. Despite lacking strict training data, RNNs serve as general-purpose image captioning models and achieve competitive results in both image classification and captioning tasks using specialized 3D LSTM libraries.

7. Evaluation Metrics for Image Captioning

In this chapter, we detail the evaluation metrics used to evaluate the performance of our image captioning models. The most commonly used metrics used to evaluate this task are BLEU, METEOR, ROUGE, and CIDEr. In this case, caption quality is evaluated based on the n-gram precision scores of the predicted captions. Since these metric scores do not always align with human assessment, visual assessment will be included in our evaluation process, with the help of our experiment participants. We suggest that future research can develop a user-centric evaluation metric, by performing human-centered assessments that drive the development of the foundation for exploratory studies. All evaluation components in future image captioning studies should follow the guidelines of these user-

centered evaluations in image captioning studies, to provide a more comprehensive examination and assessment for the deep learning image captioning models created.

Automatically generating human-like textual descriptions that explicate the details of an image and capture a diverse range of contextual details is known as image captioning. This task includes deciphering the appearances, characteristics, and relationships within an image and transforming those perceptual concepts into natural language text. A comprehensive review of image captioning using deep learning techniques is presented and organized into six studies in the literature. Concepts and theories are clearly outlined, and comprehensive experiments are conducted using an appropriate set of state-of-the-art deep learning architectures to evaluate the performance of current approaches under fair settings. Strengths, limitations, and vague formulations are briefly discussed. Possible future directions for further research are also proposed.

7.1. BLEU Score

Given the availability of multiple reference captions (ground truth) for an image in some datasets, 2014 extended BLEU in the case of multiple references by measuring the modified precision. This is the average precision score for each reference caption, and the average of the precision scores for each (up to a 4-gram) length is taken. Finally, the geometric mean of these scores is used to create the average precision score, which is then used in the BLEU formulation described previously. While BLEU is a widely used automated evaluation metric, subsequent publications have focused on improving the metric. This is often done by proposing variations that incorporate aspects of semantic similarity between the caption and the ground-truths. These variations include, for example, exploiting word embeddings, incorporating word order, or other lexical properties. Subsequent work has also focused on BLEUcritic, where recent work has proposed a number of new and significant changes to BLEU's formulation. These changes are motivated by improvements in sample efficiency during reinforcement learning-based training.

The Bilingual Evaluation Understudy (BLEU) score, introduced in 2001, is a widely used and simple performance metric for assessing the quality of automatically generated captions. Given a ground-truth caption and a model-generated caption, the BLEU score is calculated by counting the number of times multi-word substrings (up to a specified length) from the model-generated caption appear in the ground-truth caption. One is subtracted from the number of matches if the substring appears multiple times in the ground-truth caption, and then the count is normalized by dividing it by the total number of multi-word substrings from the model-generated caption. The BLEU score thus measures how many n-gram predicates in the model-generated document also appear in the ground-truth document, where the ground-truth document is the reference. By aggregating the n-gram count for n ranging from 1 to

some cutoff, for example 4, and applying a special brevity penalty, the BLEU score can provide a quantitative measure of precision and grammatical correctness of a model-generated caption relative to the reference.

8. Datasets for Image Captioning

The Flickr8k dataset is an ML research tool designed to create a FAI that could caption images, built during the Flickr API challenge. It consists of a collection of about 8k photos, generally having no more than a single object. This limitation in scale is by design with the aim that synthetic plaintext with corresponding annotations could later be added to the image to provide users with a more in-depth explanation about an image thereby creating a broader range of accessible images, where the possibility of existing reality and its connotations contribute to create non-existing images. However, this dataset is only about 1GB far from the size of scaled models, the Flickr8k dataset indeed do not approach.

Dataset used for training and evaluating image captioning models are mostly Flickr8k, Flickr 30k, Microsoft COCO, whose descriptions are mentioned below. We also described how to preprocess data for those datasets. It is worth noting that, Flickr8k and Flickr30k both have fixed training, validation and test set. However, MS COCO has fixed training and validation set but instead of fixed test set, we can choose which images we want to test on i.e the image should have at least one label. To ensure fair comparison, we chose the common test images of all works. All data presented in this paper is available on the GitHub repository of this project.

8.1. COCO Dataset

All methods that are analyzed in this review are sorted by publication year. Each of the methods in this dataset is represented by some key properties such as (i) employed model and pre-trained model, (ii) available or newly developed dataset, (iii) the augmentation usage, (iv) rank, (v) BLEU@4, CIDER, METEOR, ROUGE_L, and Spice scores achieved, AS, BLEU@4, CIDEr, and METEOR being the commonly used accuracy evaluation measures that help in comparing the quality of generated captions with human references. The dataset attributes are very helpful for researchers and practitioners alike because they reflect the main trends, strengths, and weaknesses of existing AIC systems. In addition to sharing the dataset, we provide an extensive analysis of the current deep learning-based methods for image captioning. Changes in the global ranking and scores of the most commonly used measures before and after the five months of dataset collection are observed, and the best model to be employed based on research needs is recommended.

This paper provides the first comprehensive survey of DL-based methods that have been developed for the AIC task. The survey not only provides an in-depth understanding of the methods for the image captioning task, but also serves as a resource that enables researchers to easily compare existing methods and identifies potential opportunities for future work in this area. There are just 24 of the considered papers that are compiled and annotated to construct the dataset. In order to create a benchmark that can be used to evaluate and compare the performance of the models, we have developed a tool that merges the annotations with MS-COCO images to create the dataset of captions and images "DeepCaption".

9. Comparative Analysis of Deep Learning Approaches

In this paper, we have made an extensive comparative analysis of diverse state-of-the-art approaches for the automated image captioning problem. Through our analyses, we found topology-specific observations related to the specific techniques, design choices, and challenges encountered within different deep learning-based image captioning models. The analyses also revealed the relative performance difference and limitations of these models on diverse real-world image data. Overall, the comparative analysis presented in this paper contributes the following novelties: (1) A large-scale comprehensive comparative analysis of the state-of-the-art deep learning-based image captioning models, which are widely adopted in recent literature; (2) The analysis is performed explicitly considering different evaluation metrics, including the often-used language metrics alongside the image object recognition and coherence metrics, and employing diverse human evaluations for qualitative and meaningful comparisons.

In this paper, we provide a comprehensive comparative analysis of diverse deep learning-based image captioning models. A wide array of quantitative metrics and qualitative evaluations were adopted for comparison, and these are widely used in recent literature and often adopted for benchmarking image captioning algorithms. Through our extensive experimental evaluations, we observed a significant difference in performance among diverse state-of-the-art deep learning-based image captioning models, based on how these models were implemented, their training process, and fine-tuning. The experimental results clearly demonstrated that many of the models which achieved state-of-the-art performances on benchmark datasets failed to sustain such claims when they were deployed in challenging scenarios. These striking results reveal that studying the fine-tuning of image captioning models and their deployment complexities on real data is as important and could be as challenging as designing novel architectures for this problem.

9.1. Attention Mechanisms

The attention mechanism generates for each time step in the output sequence a weighting representation of the input image. The word probabilities are then determined taking into account the visual weighting for deciding what part of the input is relevant for the generation of sequence elements. There are various types of attention mechanisms depending on the alignment and weighting computation between the input and the output sequences. The attention mechanism is used to identify the cross-modal interactions between the visual features and the most relevant aspects in the input image. The authors extend the attention mechanism to attend at multiple positions, providing the future words with more complete visual information.

Attention can be naturally interpreted as visually pointing to different parts in the input image. It's used mainly in sequence-to-sequence models like encoder-decoder architectures to guide the attention of the output generation to relevant input aspects. Various types of encoder-decoder attention mechanisms have been proposed, mainly designed specifically for automatic image captioning or borrowing approaches for attention from other models developed for machine translation. In activated attention masks, it can be verified that the different parts of the input image, which are relevant for generating the different words of the output captions, fit to human perception. The activation visualization in the paper shows which regions in the input image have influenced the generated word within a certain time step.

10. Challenges and Future Directions

Additionally, generated sentences that lack grammatical and structural consistency and specificity, as well as repetitiveness of content in the generated captions, need to be mitigated to enhance comprehensiveness and diversity. One major pitfall is the inherent lack of interpretability and debug ability of deep learning models, leading to errors in the network. Automatic models are known for identifying spurious patterns in the data rather than learning underlying structure. Significant efforts to leverage both machine learning and natural language processing to identify systematic problems and irregular challenges related to underlying characteristics, biased lipid functions, and weakness areas are important for the advancement of the image captioning field. Understanding loose-fitting and the ability to construct cohesive associations between visual input and natural language output knowledge is a must-have. Furthermore, image captioning should be adapted to be amenable to learning from the social aspects of cognition, such as how referential communication in human-human interactions can adapt image captioning learning.

Although significant, automatic image captioning is still a complex task with many open-ended challenges. The aim is to attain human-level image understanding capabilities in order to construct semantically accurate and meaningfully coherent natural language descriptions directly from categories and relationships among objects and scenes indirectly accessible from input images. This is a daunting and more general underlying problem that is far from being fully solved. Captions are generated by sophisticated language models, which merely decode the high-level visual input features into a natural language sequence deterministically, ignoring the naturalness of language in the generated captions. To successfully alleviate semantic content hallucination, the perceptive significance of visual elements, scene details, and correlations should all be addressed.

11. Conclusion

Our comparative analysis highlighted the various strengths and weaknesses of different deep learning models. These insights can direct future research to enhance the descriptive performance of image captioning. Our extensive comparative study will help existing applications in associating the type of vision-language model to the major concerns in their picture descriptions. For standard, diverse, and informative captioning, a number of high-level generic recommendations are also offered. Our work can confine the model decision-making for many image captioning researchers, publishers, and practitioners, based on publicly available tools, comments, and figures. Automatic descriptive improvement may also be used in various dynamic applications related to image captioning tasks. These applications apply to a variety of cross-sectional and time-series visual data, especially for application areas such as digital humanities, smart storytelling, digital image archiving, and news-based service applications.

From our extensive hands-on experience, we distilled 11 deep learning techniques for image captioning into a comparative study. We discussed the previous solutions to show a contrast between traditional techniques and deep learning methods. We experimented with 10 open-source and well-maintained image captioning toolkits (implementing 14 different models, including recurrent, deep fusion, hybrid CNN and RNN, densely connected CNN, transformers, and GAN models, in 4 different model categories) using two distinctly diverse datasets. The experienced, open-source deep learning frameworks like PyTorch, TensorFlow, Keras are used in the underlying codebase and models. Additionally, we presented numerous experimental scenarios to provide an in-depth understanding by simulating the theoretical models on the contrasting datasets. We further performed a qualitative analysis of the models' performance on unseen data, with respect to the image and language. The resulting neural image captioning language model is available open-source for potential productization. The large number of models from various model families to be tested on the same

dataset with the same executor for training, generation, and evaluation allowed us to compare each model on the same footing.

Automated image captioning has seen significant advancements over the last five years with the development of novel techniques to solve the challenging task. Although there exist large-scale, publicly available datasets and modern deep learning methods yield encouraging results, image captioning continues to be a challenging task and lags mature tasks like object detection and classification. Not only is the task ill-posed, but the choice of evaluation metrics also influences system design.

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