Recent, rapid advancement in visual question answering architecture: a review

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Abstract

Understanding visual question answering is going to be crucial for numerous human activities. However, it presents major challenges at the heart of the artificial intelligence endeavor.

This paper presents an update on the rapid advancements in visual question answering using images that have occurred in the last couple of years. Tremendous growth in research on improving visual question answering system architecture has been published recently, showing the importance of multimodal architectures. Several points on the benefits of visual question answering are mentioned in the review paper by Manmadhan et al. (2020), on which the present article builds, including subsequent updates in the field.

Introduction

Image understanding has been one of the primary drivers of artificial intelligence research and development over the years. In the healthcare sector, much of many physicians' practices depend on diagnostic radiology such as CT, PET, MRI, X-rays, etc. Pathology is widely used to make the initial diagnosis, but nevertheless medical images help in a major way for physicians to identify and treat health problems. For cancer tumors, lab results might not tell if the patient has a tumor in the lung or brain. Using radiology images, doctors can often much more clearly identify the presence and location of tumors in human body. Artificial intelligence is sometimes considered an exponential technology, and has advanced greatly in just a couple of decades, including speeding up tremendously in the last few years, due especially to advances in AI algorithms. This paper is written to provide an understanding of recent advancement in visual question answering (VQA). Newer techniques in both the image understanding and natural language understanding (NLU) subfields of AI have been helping to enable progress in visual question answering. The focus has been on connectionist approaches, in particular their recent and rapidly improving models. Thus, application of the deep learning approach to connectionism has been widely studied in the fields of speech recognition, drug design, precision medicine, disease detection, health surveillance, health care, image classification, etc.

The Visual Question Answering Concept

Visual question answering involves both computer vision and natural language processing, exemplifying what is commonly referred to as multi-model tasks. In visual question answering, the model is trained to output a correct answer for an image and a related question. Figure 1 shows an example of visual question answering.

![Figure 1. Example picture of VQA on images (Source — VQA: Visual Question Answering, visualqa.org).](image-url)

Figure 2 shows a schematic of the visual question answering process. The objective of visual question answering is to predict the answer to a question about an image.
Deep learning research has produced several new techniques in VQA. Figure 3 illustrates that there were very few research papers/articles until 2015. The data for the graph is from a search query qualified by year in Google Scholar on the query “visual question answering.” After 2017 the growth in the research work has increased dramatically. The number of research papers increased from 73 to 3,400 per year between year 2015 and 2021, more than a 40-fold increase in six years. Clearly, interest in visual question answering is currently in a period of explosive growth.

The trend in recent years shows that there are numerous papers being published at an increasing rate dealing with visual question answering. Most of these papers involved non-medical images. Visual question answering on medical images is challenging due to the often-low resolution nature of these images and the frequent complexity of interpreting medical images. Manmadhan et al. (2020) covered this aspect in more detail and their observations remain relevant today.

Manmadhan et al. 2020 has written about the state of art of visual question answering, covering some of the key techniques used. However, the most recent article it cites is from June 2019 (Zhao et al.). The current article attempts to provide information on newer contributions not covered in Manmadhan et al. due to the rapid advancement in the field of visual question answering since then including the significant newer techniques that have been designed and developed.

## Medical Datasets

VQAMed (2021) provides medical images and question answer datasets. Figure 4 illustrates the numbers of words in each answer from the 2019 VQAMed image dataset.

The complexity of providing an accurate answer increases with the number of words in the answer.

## Resources

Some medical image datasets available online are the following:

1. **OASIS Brains (Open Access Series of Imaging Studies)**. OASIS Brains are a multi-modal neuroimaging dataset available at OASIS (2007).

2. **The Cancer Imaging Archive (TCIA 2022)**. TCIA is a publicly available archive of medical images of cancer. The images contain different modality images such as MRI, CT etc. The images are in DICOM format.

3. **The Cancer Genome Atlas Lung Adenocarcinoma (TCGA-LUAD)**. The Cancer Genome Atlas Lung Adenocarcinoma,
introduced by Brad et al. (2016) provides clinical images.

4. **The SICAS Medical Image Repository.** SICAS (2022) is large repository of medical images such as CT, microCT, etc.

Prominent relevant image models trained on very large medical image datasets include the following:

1. **ImageNet.** ImageNet (2010) is an image dataset containing millions of labeled and sorted images.

2. **CheXNet.** CheXNet (Rajpurkar 2010) is a 121-layer DenseNet trained on ChestX-ray14 for pneumonia detection.

The following are some of the VQA datasets available:

1. **DAQUAR.** DAtaset for QUestion Answering on Real-world images introduced by Ghahramani el al. (2014).

2. **COCO-QA.** COCO is a large-scale object detection, segmentation, and captioning dataset introduced by Lin et al. (2015).

3. **Visual7W.** Visual7W is a large visual question answering (QA) dataset introduced by Zhu el al. (2016).

4. **VQAMed.** VQAMed (2021) is a medical dataset available in the ImageCLEFF website that contains medical images with questions and answers. The VQAMed dataset is available for different years starting in 2018.

**Extracting image features**

The following are commonly used architectures for image feature extraction.

1. **DenseNet.** DenseNets, short for Dense Convolutional Networks, were introduced by Huang et al. (2016). A DenseNet feed-forward connects every layer to all the other layers.

2. **VGG16/VGG19.** VGG is convolution neural network introduced by Simonyan et al. (2015).

3. **RestNet (Residual Network).** RestNet is based on a residual learning framework introduced by He et al. (2015).

4. **AlexNet.** AlexNet is a deep convolution neural network that was introduced by Krizhevsky et al. (2012). AlexNet was the first CNN to use GPUs to improve performance.

5. **GoogleNet.** GoogleNet is a convolution neural network introduced by Szegedy et al. (2014). The primary focus of the architecture is improving the utilization of computer resources.

Figure 5 illustrates architectures for visual question answering based on research papers found online. The data for the graph was from searches on Google Scholar using the search queries is on terms such as Densenet121, VGG16, VGG19, RestNet, AlexNet and GoogleNet.

![Figure 5. Percentage usage of models. (Source: Google Scholar)](image)

**Question embedding**

1. **One-hot encoded vector.** One-hot vector encoding was one of the initial methods used in natural language processing for question
embedding. More about one hot vector encoding is explained in DeepAI (2019).

2. **Bag of words (BOW).** BOW is a simple method for characterizing text data and is relatively straightforward to implement. Zhang et al. (2010) explain BOW in more detail.

3. **Word2Vec.** Word2Vec is accomplished using the skip-gram and continuous bag of words (CBOW) methods. The key aspect of the Word2Vec approach is to group similar words. Church (2017) explains the Word2Vec in detail.

4. **Global Vectors (GloVe).** The GloVe unsupervised learning algorithm was designed to incorporate global word co-occurrence statistics in its vector encodings. Pennington et al. (2014) provide the GloVe method and explain the method.

5. **Embedding from language (ELMo).** Peters et al. (2018) developed the ELMo method for text data embedding. ELMo is a natural language processing framework developed by AllenNLP. ELMo word vectors are calculated using a two-layer bidirectional language model. In a bidirectional language model, word prediction is based on both the preceding and following words.

![Embedding methods usage](image)

Figure 6. Percentage usage of several word embedding methods. (Source: Google Scholar, search result is based on: “one hot encoding”, GloVe, Word2Vec and BOW.)

**Earlier VQA research**

Manmadhan et al. (2020) covered numerous developments until June of 2019. We begin by supplementing that and also include mentions of early work. The year 2015 is foundational for visual question answering. Here are several VQA methods proposed since 2015.

Geman et al. (2015) addresses a visual Turing test to predict single answers such as yes/no for questions on images. The Turing test model however turns out to be limited in its applicability to the problem of AI for VQA.

Antol et al. (2015) introduced the concept of visual question answering on images using computer vision and natural language processing on free form and open-ended questions. Their research encompasses multi-modal and multi-discipline artificial intelligence and appears to be one of the first studies to address a multi-modal approach to visual question answering.

Antol et al. (2015) introduces goal driven, free form, open-ended visual question answering. Goal driven tasks develop a model for a specific application, such as helping the visually impaired or monitoring video images for security. Free form text in this context is text that does not have a particular structure. Open-ended questions are characterized by lack of constraints on the type of answer expected, while open-ended answers are distinguished from multiple-choice answers by being much more unconstrained. In multi-modal learning, different modes like visual, voice, textual, etc. are used. Research is characterized as multi-modal whenever the research includes multiple such modalities. Multi-modal applications include not only visual question answering, but also includes image captioning, visual descriptions, etc. The study includes a comparison between image captioning and image question answering.

**Encoder Decoder**

The encoder decoder model was found to be an improved solution for certain natural language processing tasks, in particular for transfer learning from pretrained models.

Kafle et al. (2016) experimented with the encoder decoder model using recurrent neural network (RNN) with gated units on image datasets such as COCO (Common Object in CONtext) and DAQUAR (DAataset for QUestion Answering on Real-world images).

Later, the encoder decoder based Long Short-Term Memory (LSTM) model has gained popularity
and can provide better accuracy. Avi (2016) experimented with LTSM + CNN and showed that it has outperformed other models tested in the paper.

VQA Approaches

The following are some of the VQA approaches used in the early research on visual question answering:

1. **Stacked Attention Network (SAN).** SAN is for image question answering using a question semantic representation introduced by Yang et al. (2016).

2. **Multi-Modal Factorized Bilinear Pooling (MFB).** Introduced by Fukui et al. (2016), MFB combines multi-modal features for visual question answering. Fukui et al. combines MFB and co-attention learning. This architecture is compared with bilinear pooling approaches.

3. **Answer Type Prediction.** Kafle et al. (2016) introduced an approach to answer type prediction using a combination Bayesian framework and discriminative model.

4. **Fact Based VQA.** Fact based VQA is introduced by Wang et al. (2016) and the model relies on excluding questions that require factual knowledge to answer.

5. **Attention Based VQA.** Chen et al. (2015) introduced the attention based configurable convolution neural network model.

6. **Focus Regions for VQA.** Shih et al. (2016) introduced a method based on learning select image regions relevant to the annotated question and answer.

7. **A Focused Dynamic Attention Model (FDA) for VQA.** FDA was introduced by Ilievski et al. (2016) to better align representations of image content with proposed questions.

8. **Dual Attention Network for Visual Question Answering.** Introduced by Xu et al. (2016), a uniqueness of this paper is in applying attention to both images and question features for VQA unlike other attention models that focus attention on images.

9. **Structured Attention for VQA.** Structured attention for VQA was introduced by Zhu et al. (2017) and proposed a visual attention model that is based on a multivariate distribution over a grid structured conditional random field on image regions.

10. **Graph-Structured Representation of VQA.** Teney et al. (2017) introduced a graph-structured representation model based on building graphs over scene objects and question words, and processing them using the structure of these representations.

11. **Feature Embedding for Visual Question Answering.** Lu et al. (2018) introduced this approach combining visual attention on free-form regions and multiplicative feature embedding.

12. **Semantically Guided VQA.** Zhao et al. (2018) introduced semantically guided VQA which applied multiple instances learning to extract visual representations, including entities such as actions and colors.

13. **Deep Modular Co-Attention Networks for VQA.** Deep Modular Co-Attention Networks for VQA were introduced by Yu et al. (2019) and the model is based on having deep modular co-attention layers. Each layer supports question-guided attention to images using a modular composition of two basic attention units.

**VQA approaches in 2019**

There was great progress in VQA research in 2019 and most of that research involved transformers. Key to 2019’s advances was improvements in Bidirectional Encoder Representations from Transformers (BERT) for natural language processing. Researchers introduced unique methods for applying this approach to VQA. Innovative new methods such as co-attention transformers, large-scale transformer models that consists of three encoders, the cross-modality model with self-attention and cross-attention layers, and modification of the original BERT by assigning new elements such visuals defined by regions of interest in images and linguistic elements as inputs. Identifying regions of interest can help algorithms speed up object detection. The attention concept continued to bear fruit,
such as with self-attention within a transformer, and encoding images into graphs to model inter-object relations using a graph attention mechanism.

The following are some of the most influential relevant articles of the year.

1. **ViLBERT: Pretraining Task-Agnostic Visiolinguistic Representations for Vision-and-Language Tasks.** Lu et al. (2019) introduced the ViLBERT “model for learning task-agnostic joint representations of image content and natural language.”

2. **LXMERT: Learning Cross-Modality Encoder Representations from Transformers.** Tan et al. (2019) introduced the LXMERT framework to “learn vision and language associations with a transformer model consisting of three encoders.”

3. **VI-bert: Pre-Training of Generic Visual-Linguistic Representations.** Su et al. (2019) introduced generic representations for linguistic tasks adopting a transformer model. According to the authors of article, “the backbone of VL-BERT is [a] (multi-modal) Transformer attention module taking both visual and linguistic embedded features as input.”

4. **Visualbert: A Simple and Performant Baseline for Vision and Language.** Li et al. (2019) introduced a “flexible framework for modeling a broad range of vision and language tasks consisting of a stack for transformer layers.”

5. **Relation-Aware Graph Attention Network for Visual Question Answering.** Li et al. (2019) introduced “relation aware graph attention network which encodes each image into graph and models multi-type inter object relation via a graph attention mechanism.”

**VQA approaches in 2020**

In year 2020, a variety of new models for VQA were introduced. Influential articles described models using methods such as grid-based convolutional features for VQA, bottom-up top-down models and ensemble-based models. Also used were simple CNN+LSTM models, an attention-based model strategy and a compositional model approach. A new method introduced multi-objective visual relationship detection. Another interesting concept that was introduced is mutations of inputs (questions and images).

The following are some of most visible articles published in the year 2020.

1. **In Defense of Grid Features for Visual Question Answering.** Jiang et al. (2020) revisits grid-based convolution features for VQA.

2. **Counterfactual Samples Synthesizing for Robust Visual Question Answering.** Chen et al. (2020) introduced a framework to address “visually explainability (the model should rely on the right visual regions) and question sensitivity (the model should be sensitive to linguistic variation in questions).”

3. **Towards Causal VQA: Revealing and Reducing Spurious Correlations by Invariant and Covariant Semantic Editing.** Agarwal et al. (2020) introduced casual VQA. The method performs automated semantic image manipulations and tests.

4. **Visual Question Answering Model Based on Visual Relationship Detection.** Xi et al. (2020) introduced a model based multi-objective visual relationship detection. In this model what they call appearance features replace image features from the original object.

5. **Overview of the VQA-Med Task at ImageCLEF 2020: Visual Question Answering and Generation in the Medical Domain.** Abacha et al. (2020) provides a review of the submitted works on visual question answering on medical images.

6. **Training Paradigm for Out-of-Distribution Generalization in Visual Question Answering.** Gokhale et al. (2020) introduce a model using consistency constraints on the training goal. This permits conclusions about the effects of meaning changes in the questions.
VQA approaches in 2021

In year 2021, a wide range of articles were published and the number of articles increased significantly. Research in some of the popular articles addressed language bias, large VQA datasets, the tensor decomposition model, dynamic word vectors, text aware pretraining, bias evaluating metrics, and others. All the articles demonstrated improvements in solutions for visual question answering. The following are some of these articles.

1. **Counterfactual VQA: a Cause-Effect Look at Language Bias.** Niu et al. (2021) introduced a framework to “capture … language bias as the direct causal effect of questions on answers and reduce the language bias by subtracting the direct language effect from the total cause.” This is important for visual question answering since training on biased text will impact predictions. The author are proposing a novel method to address language bias.

2. **DocVQA: A Dataset for VQA on Document Images.** Niu et al. (2021) provided “a large scale dataset of 12,767 document images of varied types and content, over which we have defined 50,000 questions and answers.” The authors introduced DocVQA “as a high-level task dynamically driving DAR algorithms to conditionally interpret document images.” The underlying concept is to include all other contents in a document besides regular text.

3. **DecomVQANet: Decomposing Visual Question Answering Deep Network Via Tensor Decomposition and Regression.** Bai et al. (2021) introduced DecomVQANet “to conduct various decomposition methods and regression strategies on different layers, including Canonical Polyadic, Tucker, and Tensor Train to decompose fully connected layers in CNN and LSTM” networks.

4. **Joint Embedding VQA Model Based on Dynamic Word Vector.** Ma et al. (2021) introduced this approach and, according to the article, dynamic word vectors outperform static word vectors on the visual question answering task.

5. **TAP: Text-Aware Pre-Training for Text-VQA and Text-Caption.** Yang et al. (2021) introduced TAP, in which the basic methodology is to use scene text in a pretraining model and later fine tune to improve the model.

6. **Roses Are Red, Violets Are Blue... but Should VQA Expect Them To?** Kervadec et al. (2021) proposed “a new fine-grained re-organization of the GQA dataset and a set of the respective evaluation metrics allowing to precisely evaluate the reasoning behavior of VQA models.”

**Transformers**

Transformers were introduced by Vaswani et al. (2017) to improve upon some of the previous state of art solutions such as recurrent neural networks (RNN), long short-term memory (LSTM). Vaswani et al. explains the transformer model architecture and its usefulness.

**Bidirectional Encoder Representations from Transformers (BERT)**

BERT builds on transformers and was introduced in 2018 by Devlin et al. (2019). Since then, it has been used extensively for various natural language processing tasks. While encoder decoder models have sequential layers, in which basically inputs are sequences and outputs are a single number, BERT models are transformer based. BERT models are of two types: BERT base and BERT large. BERT base uses 12 encoder layers and BERT large uses 24 encoder layers.

**Vision Transformer**

Research has shown the benefits of using transformers in natural language processing. The concept has also been applied to computer vision, resulting in the vision transformer (ViT) model.

BERT’s success has opened up research directions focused on applying similar techniques on images. In the vision transformer model, the images are divided into patches, each patch with size 16x16 pixels. Vision transformers were introduced by Dosovitskiy et al. in 2021. The authors found that images divided into a sequence of patches and processed by a transformer performed better for image classification tasks. Figure 7 gives an example of creating image patches from a single image.
Swin Transformers

Liu et al. (2021) introduced swin transformers to overcome challenges in using transformers for computer vision. Swin transformers are improved compared to vision transformer, which themselves are improved over CNNs.

Liu et al. introduced the swin transformer to overcome challenges in adapting transformers to vision. Liu et al. found that the swin transformer architecture applied to ImageNet had higher accuracy compared to other architectures.

Conclusions

We are continuing to see a vigorous upward trend in development of visual question answering systems since the trend became evident in 2015. The state of art in visual question answering is changing rapidly each year with multiple improved architectures being proposed. In the year 2015, it was the deep neural networks models that were the state of art. They have given way to the much more efficient transformer architectures, which are themselves experiencing rapid Vita progress. According to Lu (2020), artificial intelligence is progressing rapidly in a way that the massive need for computing resource is likely to bring back Moore’s Law back to life. The newer methods such a BERT and ViT have been found to be fast to train compared to more traditional neural networks.

Replicating results has been found to often be difficult or impossible in science (Haele 2021) and there are a number of different reasons why this might be true for a given report. These include that the architecture might not be sufficiently explained, all the steps might not be defined, etc. Although this problem is unlikely to be resolved in the near future for science in general, and can only impeded progress according to standard views of scientific progress, it is clear that AI and, specifically, VQA have nevertheless been undergoing rapid advancements in recent years and there is little indication at present of any upcoming limit to continued progress.

References

Sruthy Manmadhan and Binsu C. Kavoor. 2020. Visual question answering: a state-of-the-art review. https://link.springer.com/article/10.1007/s10462-020-09832-7.

Chien-Ping Lu. 2020. AI, Native Supercomputing and the Revival of Moore’s Law. https://link.springer.com/article/10.1007/s10462-020-09832-7.

Tara Haele. 2021. A massive 8-year effort finds that much cancer research can’t be replicated. https://www.sciencenews.org/article/cancer-biology-studies-research-replication-reproducibility.

Stanislaw Antol, Aishwarya Agrawal, Jiasen Lu, Margaret Mitchell, Dhruv Batra, C. Lawrence, Zitnick and Devi Parikh. 2015. VQA: Visual Question Answering. https://arxiv.org/pdf/1505.00468.pdf.

Donald Geman, Stuart Geman, Neil Hallonquist and Laurent Younes. 2015. Visual Turing test for computer vision systems. National Academy of Sciences, https://www.pnas.org/content/112/12/3618.full.pdf.

Ze Liu, Yutong Lin, Yue Cao, Han Hu, Yixuan Wei, Zheng Zhang, Stephen Lin and Baining Guo. 2021. Swin Transformer: Hierarchical Vision Transformer using Shifted Windows. https://arxiv.org/pdf/2103.14030.pdf.

Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, Jakob Uszkoreit and Neil Houlsby. 2021. An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale. https://openreview.net/forum?id=YicbFdNTTy.

Kushal Kafle and Christopher Kanan. 2016. Answer-Type Prediction for Visual Question Answering. IEEE Conference on Computer Vision and Pattern Recognition. https://openaccess.thecvf.com/content_cvpr_2016/papers/Kafle_Answer-Type_Prediction_for_CVPR_2016_paper.pdf.

Avi Singh. 2016. Deep learning for visual question answering. Facebook AI Research. http://home.iitk.ac.in/~avisingh/cs671/project/report.pdf.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser and Illia Polosukhin. 2017. Attention is all you need. In Proceedings of the 31st International Conference on Neural Information Processing Systems.
DeepAI, One hot encoding. 2019. What is One-Hot Encoding? https://deepai.org/machine-learning-glossary-and-terms/one-hot-encoding.

Wei Zhao, Haiyun Peng, Steffen Eger, Erik Cambria and Min Yang. 2019. Towards Scalable and Reliable Capsule Networks for Challenging NLP Applications. https://arxiv.org/pdf/1906.02829.pdf.

ImageNet. 2010. https://www.image-net.org.

Pranav Rajpurkar, Jeremy Irvin, Kaylie Zhu, Brandon Yang, Hershel Mehta, Tony Duan, Daisy Ding, Aarti Bagul, Curtis Langlotz, Katie Shpanskaya, Matthew P. Lungeren and Andrew Y. Ng. 2010. CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning. https://stanfordmlgroup.github.io/projects/chexnet.

Mateusz Malinowski and Mario Fritz. 2014. A Multi-World Approach to Question Answering about Real-World Scenes based on Uncertain Input. https://arxiv.org/abs/1410.0210.

Tsung-Yi Lin, Michael Maire, Serge Belongie, Lubomir Bourdev, Ross Girshick, James Hays, Pietro Perona, Deva Ramanan, C. Lawrence Zitnick and Piotr Dollár. 2015. Microsoft COCO: Common Objects in Context. https://cocodataset.org/#home.

Yuke Zhu, Oliver Groth, Michael Bernstein and Fei-Fei Li. 2016. Visual7W: Grounded Question Answering in Images. https://ai.stanford.edu/~yuke/visual7w.

OASIS Brains. 2007. OASIS Brain Project. https://www.oasis-brains.org/#data.

TCIA. The Cancer Imaging Archive. https://www.cancerimagingarchive.net.

Albertina Brad, Mark Watson, Chandra Holback, Rose Jarosz, J. Keith Smith, Shanah Kirk, John Lemmerman and Kimberly Reiger-Christ. 2016. Radiology Data from The Cancer Genome Atlas Lung Adenocarcinoma [TCGA-LUAD] collection. The Cancer Imaging Archive. http://doi.org/10.7937/K9/TICIA.2016.GNJHEP5.

The SICAS Medical Image Repository. The SICAS Medical Image Repository is the place for you to store medical research data. https://www.smir.ch.

Zichao Yang, Xiaodong He, Jianfeng Gao, Li Deng and Alex Smola. 2016. Stacked Attention Networks for Image Question Answering. https://openaccess.thecvf.com/content_cvpr_2016/papers/Yang_Stacked_Attention_Networks_CVPR_2016_paper.pdf.

Akira Fukui, Dong Huk Park, Daylen Yang, Anna Rohrbach, Trevor Darrell and Marcus Rohrbach. 2016. Multimodal Compact Bilinear Pooling for Visual Question Answering and Visual Grounding. https://arxiv.org/abs/1606.01847.

Kushal Kafle and Christopher Kannan. 2016. Answer-Type Prediction for Visual Question Answering. https://openaccess.thecvf.com/content_cvpr_2016/papers/Kafle_Answer-Type_Prediction_for.CVPR_2016_paper.pdf.
Peng Wang, Qi Wu, Chunhua Shen, Anton van den Hengel and Anthony R. Dick. 2016. Fact-based Visual Question Answering. Http://arxiv.org/abs/1606.05433.

Kan Chen, Jiang Wang, Liang-Chieh Chen, Haoyuan Gao, Wei Xu and Ram Nevatia. 2015. An Attention Based Convolutional Neural Network for Visual Question Answering. Http://arxiv.org/abs/1511.05960.

Kevin J. Shih, Saurabh Singh and Derek Hoiem. 2016. Where to Look: Focus Regions for Visual Question Answering. Https://openaccess.thecvf.com/content_cvpr_2016/papers/Shih_Where_to_Look_CVPR_2016_paper.pdf.

Ilija Ilievski, Shuicheng Yan and Jiashi Feng. 2016. A Focused Dynamic Attention Jun Yu, Yuhao Cui, Dacheng Tao and Qi Tian. 2019. Deep modular co-attention networks for visual question answering. Https://openaccess.thecvf.com/content_CVPR_2019/html/Yu_Deep_Modular_Co-Attention_Networks_for_Visual_Question_Answering_CVPR_2019_paper.html.

Jiasen Lu, Dhruv Batra, Devi Parikh and Stefan Lee. 2019. Pretraining task-agnostic visiolinguistic representations for vision-and-language tasks. Https://proceedings.neurips.cc/paper/2019/file/c74d97b01eae257e44a9d5bade97baf-Paper.pdf.

Hao Tan and Mohit Bansal. 2019. LxMert: Learning cross-modality encoder representations from transformers. Https://arxiv.org/pdf/1908.07490.pdf?ref=https://github help.com.

Weijie Su, Xizhou Zhu, Yue Cao, Bin Li, Lewei Lu, Furu Wei and Jifeng Dai. 2019. Vi-bert: Pre-training of generic visual-linguistic representations. Https://arxiv.org/pdf/1908.08530.pdf.

LH Li, M Yatskar, D Yin, CJ Hsieh and KW Chang. 2019. A simple and performant baseline for vision and language. Https://direct.mit.edu/tacl/article/doi/10.1162/tacl_a_00266/43511.

Linjie Li, Zhe Gan, Yu Cheng and Jingjing Liu. 2019. Relation-Aware Graph Attention Network for Visual Question Answering. Https://openaccess.thecvf.com/content_ICCV_2019/html/Li_Relation-Aware_Graph_Attention_Network_for_Visual_Question_Answering_ICCV_2019_paper.pdf.

Huaizu Jiang, Ishan Misra, Marcus Rohrbach, Erik Learned-Miller and Xinlei Chen. 2020. In Defense of Grid Features for Visual Question Answering. Https://openaccess.thecvf.com/content_CVPR_2020/papers/Jiang_In_Defense_of_Grid_Features_for_Visual_Question_Answering_CVPR_2020_paper.pdf.

Long Chen, Xin Yan, Jun Xiao, Hanwang Zhang, Shiliang Pu and Yueting Zhuang. 2020. Counterfactual Samples Synthesizing for Robust Visual Question Answering. Https://openaccess.thecvf.com/content_CVPR_2020/papers/Chen_Counterfactual_Samples_Synthesizing_for_Robust_Visual_Question_Answering_CVPR_2020_paper.pdf.

Vedika Agarwal, Rakshith Shetty and Mario Fritz. 2020. Towards Causal VQA: Revealing and Reducing Spurious Correlations by Invariant and Covariant Semantic Editing. Https://openaccess.thecvf.com/content_CVPR_2020/papers/Agarwal_Towards_Causal_VQA_ Revealing_and_Reducing_Spurious_Correlations_by_Invariant_CVPR_2020_paper.pdf.

Yuling Xi, Yanning Zhang, Songtao Ding and Shaohua Wan. 2020. Visual question answering model based on visual relationship detection, Signal Processing: Image Communication. Https://www.sciencedirect.com/science/article/pii/S0923596519305077.

Ilija Ilievski, Shuicheng Yan and Jiashi Feng. A focused dynamic attention model for visual question answering. Http://arxiv.org/abs/1604.01485.

Huijuan Xu and Kate Saenko. 2016. Dual Attention Network for Visual Question Answering. Https://cspeople.bu.edu/hxu/ECCV16_VisStory_workshop.pdf.

Christopher Kanan and Kushal Kafle. 2016. A Bayesian Model of Visual Question Answering. Https://jov.arvojournals.org/article.aspx?articleid=2550317.

Chen Zhu, Yanpeng Zhao, Shuaiyi Huang, Kewei Tu and Yi Ma. 2017. Structured Attentions for Visual Question Answering. Https://openaccess.thecvf.com/content_iccv_2017/html/Zhu_Structured_Attentions_for_ICCV_2017_paper.html.

Damien Teney, Lingqiao Liu and Anton van Den Hengel. 2017. Graph-structured representations for visual question answering. Https://openaccess.thecvf.com/content_iccv_2017/html/Zhu_Structured_Attentions_for_ICCV_2017_paper.html.

Dongfei Yu, Jianlong Fu, Tao Mei and Yong Rui. 2017. Multi-Level Attention Networks for Visual Question Answering. Https://openaccess.thecvf.com/content_cvpr_2017/html/Yu_Multi-Level_Attention_Networks_CVPR_2017_paper.html.

Ted Zhang, Dengxin Dai, Tinne Tuytelaars, Marie-Francine Moens and Luc Van Gool. 2017. Speech-based visual question answering. Https://arxiv.org/abs/1705.00464.

Peng Gao, Hongsheng Li, Shuang Li, Pan Lu, Yikang Li, Steven C.H. Hoi and Xiaogang Wang. 2018. Question-Guided Hybrid Convolution for Visual Question Answering. Https://openaccess.thecvf.com/content_ECCV_2018/html/gao_peng_Question-Guided_Hybrid_Convolution_ECCV_2018_paper.html.
Zhou Yu, Jun Yu, Chenchao Xiang, Jianping Fan and Dacheng Tao. 2018. Beyond bilinear: Generalized multimodal factorized high-order pooling for visual question answering. https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=8334194.

Yang Shi, Tommaso Furlanello, Sheng Zha and Animashree Anandkumar. 2018. Question Type Guided Attention in Visual Question Answering. Https://openaccess.thecvf.com/content_ECCV_2018/html/Yang_Shi_Question_Type_Guided_ECCV_2018_paper.html.

Bai, Yalong and Fu, Jianlong and Zhao, Tiejun and Mei, Tao. 2018. Deep Attention Neural Tensor Network for Visual Question Answering. Https://openaccess.thecvf.com/content_ECCV_2018/html/Yalong_Bai_Deep_Attention_Neural_ECCV_2018_paper.html.

Pan Lu, Hongsheng Li, Wei Zhang, Jianyong Wang and Xiaogang Wang. 2018. Co-Attending Free-Form Regions and Detections With Multi-Modal Multiplicative Feature Embedding for Visual Question Answering. https://ojs.aaai.org/index.php/AAAI/article/view/12240.

Handong Zhao, Quanfu Fan, Dan Gutfreund and Yun Fu. 2018. Semantically guided visual question answering. Https://par.nsf.gov/servlets/purl/10065427.

Zhou Yu, Asma Ben Abacha , Vivek V. Datla, Sadid A. Hasan, Dina Demner-Fushman and Henning Muller. 2020. Overview of the VQA-Med Task at ImageCLEF 2020: Visual Question Answering and Generation in the Medical Domain. Http://ceur-ws.org/Vol-2696/paper_106.pdf.

Tejas Gokhale, Pratyay Banerjee, Chitta Baral and Yezhou Yang. 2020. Training Paradigm for Out-of-Distribution Generalization in Visual Question Answering. Https://arxiv.org/abs/2009.08566.

Yulei Niu, Kaihua Tang, Hanwang Zhang, Zhiwu Lu, Xian-Sheng Hua and Ji-Rong Wen. 2021. Counterfactual VQA: A Cause-Effect Look at Language Bias. Https://openaccess.thecvf.com/content/CVPR2021/papers/Niu_Counterfactual_VQA_A_Cause-Effect_Look_at_Language_Bias_CVPR_2021_paper.pdf.

Zongwen Bai, Ying Li, Marcin Woźniak, Meili Zhou and Di Li. 2021. DecomVQA: Decomposing visual question answering deep network via tensor decomposition and regression. Https://www.sciencedirect.com/science/article/abs/pii/S0003133420303411.

Zhiyang Ma, Wenfeng Zheng, Xiaobing Chen and Lirong Yin. 2021. Joint embedding VQA model based on dynamic word vector. Https://doi.org/10.7717/peerj-cs.353.

Zhengyuan Yang, Yijuan Lu, Jianfeng Wang, Xi Yin, Dinei Florencio, Lijuan Wang, Cha Zhang, Lei Zhang and Jiebo Luo. 2021. TAP: Text-Aware Pre-Training for Text-VQA and Text-Caption. Https://openaccess.thecvf.com/content/CVPR2021/papers/Yang_TAP_Text-Aware_Pre-Training_for_Text-VQA_and_Text-Caption_CVPR_2021_paper.pdf.

Corentin Kervadec, Grigory Antipov, Moez Baccouche and Christian Wolf. 2021. Roses Are Red, Violets Are Blue... but Should VQA Expect Them To? Https://openaccess.thecvf.com/content/CVPR2021/papers/Kervadec_Roses_Are_Red_Violets_Are_Blue..._but_Should_VQA_Expect_CVPR_2021_paper.pdf.