

Visual Question Answering using Deep Learning: A Survey and Performance Analysis

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Abstract—The Visual Question Answering (VQA) task combines challenges for processing data with both Visual and Linguistic processing, to answer basic ‘common sense’ questions about given images. Given an image and a question in natural language, the VQA system tries to find the correct answer to it using visual elements of the image and inference gathered from textual questions. In this survey, we cover and discuss the recent datasets released in the VQA domain dealing with various types of question-formats and enabling robustness of the machine-learning models. Next, we discuss about new deep learning models that have shown promising results over the VQA datasets. At the end, we present and discuss some of the results computed by us over the vanilla VQA models, Stacked Attention Network and the VQA Challenge 2017 winner model. We also provide the detailed analysis along with the challenges and future research directions.

Index Terms—Visual Question Answering, Artificial Intelligence, Human Computer Interaction, Deep Learning, CNN, LSTM.

I. INTRODUCTION

Visual Question Answering (VQA) refers to a challenging task which lies at the intersection of image understanding and language processing. The VQA task has witnessed a significant progress in the recent years by the machine intelligence community. The aim of VQA is to develop a system to answer specific questions about an input image. The answer could be in any of the following forms: a word, a phrase, binary answer, multiple choice answer, or a fill in the blank answer. Agarwal et al. [1] presented a novel way of combining computer vision and natural language processing concepts of to achieve **Visual Grounded Dialogue**, a system mimicking the human understanding of the environment with the use of visual observation and language understanding.

The advancements in the field of deep learning have certainly helped to develop systems for the task of Image Question Answering. Krizhevsky et al [2] proposed the AlexNet model, which created a revolution in the computer vision domain. The paper introduced the concept of Convolution Neural Networks (CNN) to the mainstream computer vision application. Later many authors have worked on CNN, which has resulted in robust, deep learning models like VGGNet [3], Inception [4], ResNet [5], and etc. Similarly, the recent advancements in natural language processing area based on deep learning have improved the text understanding performance as well. The first major algorithm in the context of text processing is considered to be the Recurrent Neural Networks (RNN) [6]

which introduced the concept of prior context for time series based data. This architecture helped the growth of machine text understanding which gave new boundaries to machine translation, text classification and contextual understanding. Another major breakthrough in the domain was the introduction of Long-Short Term Memory (LSTM) architecture [7] which improvised over the RNN by introducing a context cell which stores the prior relevant information.

The vanilla VQA model [1] used a combination of VGGNet [3] and LSTM [7]. This model has been revised over the years, employing newer architectures and mathematical formulations. Along with this, many authors have worked on producing datasets for eliminating bias, strengthening the performance of the model by robust question-answer pairs which try to cover the various types of questions, testing the visual and language understanding of the system. In this survey, first we cover major datasets published for validating the Visual Question Answering task, such as VQA dataset [1], DAQUAR [8], Visual7W [9] and most recent datasets up to 2019 include Tally-QA [10] and KVQA [11]. Next, we discuss the state-of-the-art architectures designed for the task of Visual Question Answering such as Vanilla VQA [1], Stacked Attention Networks [12] and Pythia v1.0 [13]. Next we present some of our computed results over the three architectures: vanilla VQA model [1], Stacked Attention Network (SAN) [12] and Teney et al. model [14]. Finally, we discuss the observations and future directions.

II. DATASETS

The major VQA datasets are summarized in Table I. We present the datasets below.

DAQUAR: DAQUAR stands for Dataset for Question Answering on Real World Images, released by Malinowski et al. [8]. It is the first dataset released for the IQA task. The images are taken from NYU-Depth V2 dataset [18]. The dataset is small with a total of 1449 images. The question bank includes 12468 question-answer pairs with 2483 unique questions. The questions have been generated by human annotations and confined within 9 question templates using annotations of the NYU-Depth dataset.

VQA Dataset: The Visual Question Answering (VQA) dataset [1] is one of the largest datasets collected from the MS-COCO [19] dataset. The VQA dataset contains at least 3 questions per image with 10 answers per question. The dataset

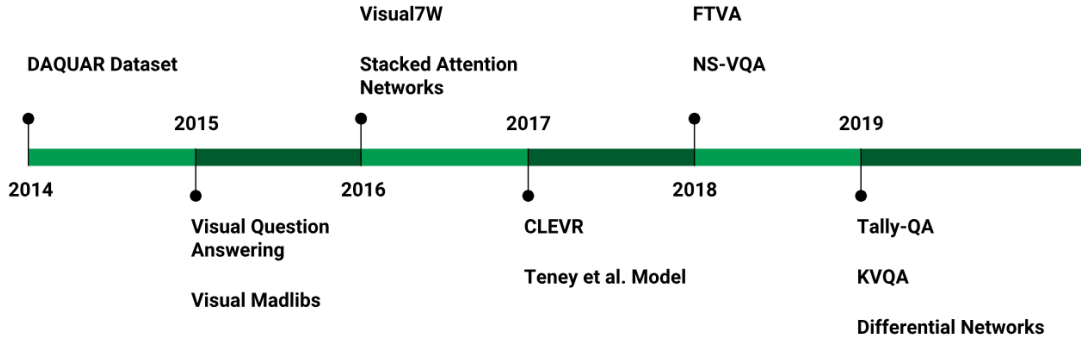


Fig. 1. The timeline of major breakthrough in Visual Question Answering (VQA) in last 5 years, ranging from DAQUAR in 2014 to Differential Networks in 2019.

TABLE I
OVERVIEW OF VQA DATASETS DESCRIBED IN THIS PAPER.

Dataset	# Images	# Questions	Question Type(s)	Venue	Model(s)	Accuracy
DAQUAR [8]	1449	12468	Object Identification	NIPS 2014	AutoSeg [15]	13.75%
VQA [1]	204721	614163	Combining vision, language and common-sense	ICCV 2015	CNN + LSTM	54.06%
Visual Madlibs [16]	10738	360001	Fill in the blanks	ICCV 2015	nCCA (bbox)	47.9%
Visual7W [9]	47300	2201154	7Ws, locating objects	CVPR 2016	LSTM + Attention	55.6%
CLEVR [17]	100000	853554	Synthetic question generation using relations	CVPR 2017	CNN + LSTM + Spatial Relationship	93%
Tally-QA [10]	165000	306907	Counting objects on varying complexities	AAAI 2019	RCN Network	71.8%
KVQA [11]	24602	183007	Questions based on Knowledge Graphs	AAAI 2019	MemNet	59.2%

Examples of VQA questions and answers:

- Is something under the table? **yes**
- Can you park? **no**
- What kind of store is this? **grocery**
- How many bikes are there? **2**
- What number do you see? **33**
- What color is the top? **white and orange**
- Is the display case as tall as it could be? **yes**
- What number is the bus? **48**
- Does this man have children? **yes**
- How many pizzas are on the plate? **1**
- How many people are on the plane? **1**
- What shape is the sign? **stop**
- Is this man crying? **no**
- What kind of cheese is on the pizza? **mozzarella**
- What is the shape of the plate? **round**
- How many balloons are there? **1**
- What shape is the sign? **stop**
- How many balloons are there? **1**
- What is the woman washing her? **door handle**
- Why is the boy on the right? **his friend is hurt**
- What is on the backseat? **nothing**
- What side of the water is the? **right**
- What side of the water is the? **right**
- What side of the water is the? **right**

Examples of Madlibs questions and answers:

- Describe the type of scene/place shown in - The place is a(n) **tennis court**.
- Describe the emotional content of this pic - When I look at this picture, I feel **hungry**.
- Describe the most interesting or unusual aspect of this picture - The most interesting aspect of this picture is **the orca**.
- Describe what happened immediately before - One or two seconds before this picture was taken **the car was white**.
- Describe what happened immediately after this picture was taken **the car was white**.
- Describe the appearance of the indicated object - The car is **white**.

Examples of Tally-QA questions and answers:

- How many giraffes are there? **2**
- How many giraffes are drinking water? **2**

Examples of KVQA questions and answers:

- Who is to the left of Hillary Clinton? **A: Amir Khan**
- What is the age gap between the two people in the image? **A: 24 years**
- How many people in this image were born in United Kingdom? **A: 2**
- Who is the founder of the political party to which person second from left belongs to? **A: Syama Prasad Mookerjee**
- Who among the people in the image were born after the end of World War II? **A: Both**

Fig. 2. Samples from VQA (1st row, 1st column), Madlibs (1st row, 2nd column), Tally-QA (2nd row, 1st column), and KVQA (2nd row, 2nd column) datasets.

contains 614,163 questions in the form of open-ended and multiple choice. In multiple choice questions, the answers can

be classified as: 1) Correct Answer, 2) Plausible Answer, 3) Popular Answers and 4) Random Answers. Recently, VQA

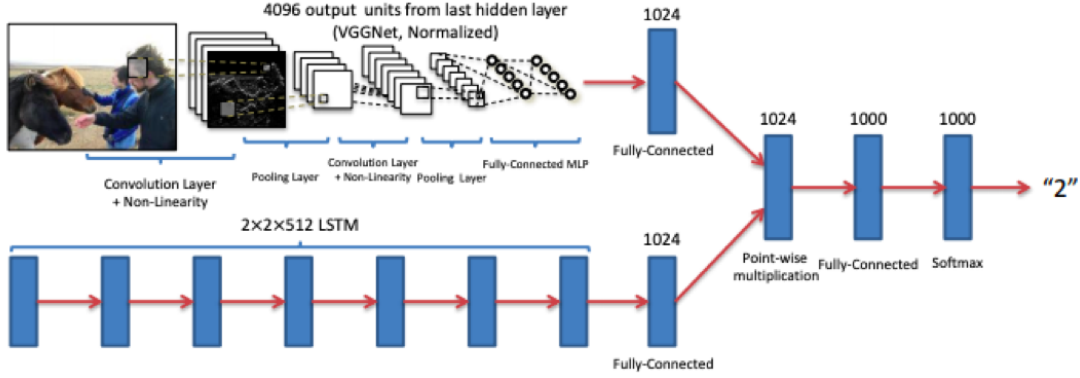


Fig. 3. Vanilla VQA Network Model [1].

V2 dataset [1] is released with additional confusing images. The VQA sample images and questions are shown in Fig. II in 1st row and 1st column.

Visual Madlibs: The Visual Madlibs dataset [16] presents a different form of template for the Image Question Answering task. One of the forms is the fill in the blanks type, where the system needs to supplement the words to complete the sentence and it mostly targets people, objects, appearances, activities and interactions. The Visual Madlibs samples are shown in Fig. II in 1st row and 2nd column.

Visual7W: The Visual7W dataset [9] is also based on the MS-COCO dataset. It contains 47,300 COCO images with 327,939 question-answer pairs. The dataset also consists of 1,311,756 multiple choice questions and answers with 561,459 groundings. The dataset mainly deals with seven forms of questions (from where it derives its name): What, Where, When, Who, Why, How, and Which. It is majorly formed by two types of questions. The telling questions are the ones which are text-based, giving a sort of description. The pointing questions are the ones that begin with Which, and have to be correctly identified by the bounding boxes among the group of plausible answers.

CLEVR: CLEVR [17] is a synthetic dataset to test the visual understanding of the VQA systems. The dataset is generated using three objects in each image, namely cylinder, sphere and cube. These objects are in two different sizes, two different materials and placed in eight different colors. The questions are also synthetically generated based on the objects placed in the image. The dataset also accompanies the ground-truth bounding boxes for each object in the image.

Tally-QA: Very recently, in 2019, the Tally-QA [10] dataset is proposed which is the largest dataset of object counting in the open-ended task. The dataset includes both simple and complex question types which can be seen in Fig. II. The dataset is quite large in numbers as well as it is 2.5 times the VQA dataset. The dataset contains 287,907 questions, 165,000 images and 19,000 complex questions. The Tally-QA samples are shown in Fig. II in 2nd row and 1st column.

KVQA: The recent interest in common-sense questions has led to the development of world Knowledge based VQA dataset [11]. The dataset contains questions targeting various categories of nouns and also require world knowledge to arrive

at a solution. Questions in this dataset require multi-entity, multi-relation, and multi-hop reasoning over large Knowledge Graphs (KG) to arrive at an answer. The dataset contains 24,000 images with 183,100 question-answer pairs employing around 18K proper nouns. The KVQA samples are shown in Fig. II in 2nd row and 2nd column.

III. DEEP LEARNING BASED VQA METHODS

The emergence of deep-learning architectures have led to the development of the VQA systems. We discuss the state-of-the-art methods with an overview in Table II.

Vanilla VQA [1]: Considered as a benchmark for deep learning methods, the vanilla VQA model uses CNN for feature extraction and LSTM or Recurrent networks for language processing. These features are combined using element-wise operations to a common feature, which is used to classify to one of the answers as shown in Fig. 3.

Stacked Attention Networks [12]: This model introduced the attention using the softmax output of the intermediate question feature. The attention between the features are stacked which helps the model to focus on the important portion of the image.

Teney et al. Model [14]: Teney et al. introduced the use of object detection on VQA models and won the VQA Challenge 2017. The model helps in narrowing down the features and apply better attention to images. The model employs the use of R-CNN architecture and showed significant performance in accuracy over other architectures.

Neural-Symbolic VQA [24]: Specifically made for CLEVR dataset, this model leverages the question formation and image generation strategy of CLEVR. The images are converted to structured features and the question features are converted to their original root question strategy. This feature is used to filter out the required answer.

Focal Visual Text Attention (FVTA) [25]: This model combines the sequence of image features generated by the network, text features of the image (or probable answers) and the question. It applies the attention based on the both text components, and finally classifies the features to answer the question. This model is better suited for the VQA in videos which has more use cases than images.

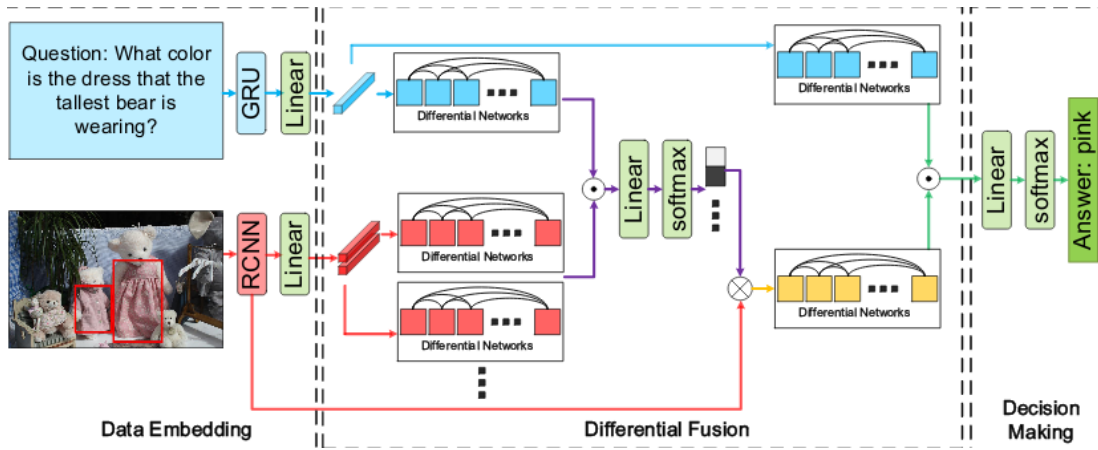


Fig. 4. Differential Networks Model [20].

TABLE II
OVERVIEW OF MODELS DESCRIBED IN THIS PAPER. THE PYTHIA V0.1 IS THE BEST PERFORMING MODEL OVER VQA DATASET.

Model	Dataset(s)	Method	Accuracy	Venue
Vanilla VQA [1]	VQA [1]	CNN + LSTM	54.06 (VQA)	ICCV 2015
Stacked Attention Networks [12]	VQA [1], DAQAUR [8], COCO-QA [21]	Multiple Attention Layers	58.9 (VQA), 46.2 (DAQAUR), 61.6 (COCO-QA)	CVPR 2016
Teney et al. [14]	VQA [1]	Faster-RCNN [22] + Glove Vectors [23]	63.15 (VQA-v2)	CVPR 2018
Neural-Symbolic VQA [24]	CLEVR [17]	Symbolic Structure as Prior Knowledge	99.8 (CLEVR)	NIPS 2018
FVTA [25]	MemexQA [26], MovieQA [27]	Attention over Sequential Data	66.9 (MemexQA), 37.3 (MovieQA)	CVPR 2018
Pythia v1.0 [28]	VQA [1]	Teney et al. [14] + Deep Layers	72.27 (VQA-v2)	VQA Challenge 2018
Differential Networks [20]	VQA [1], TDIUC [29], COCO-QA [21]	Faster-RCNN [22], Differential Modules [30], GRU [31]	68.59 (VQA-v2), 86.73 (TDIUC), 69.36 (COCO-QA)	AAAI 2019

TABLE III
THE ACCURACIES OBTAINED USING VANILLA VQA [1], STACKED ATTENTION NETWORKS [12] AND TENEY ET AL. [14] MODELS WHEN TRAINED ON VQA [1] AND VISUAL7W [9] DATASETS.

Model Name	Accuracy	
	VQA Dataset	Visual7W Dataset
CNN + LSTM	58.11	56.93
Stacked Attention Networks	60.49	61.67
Teney et al.	67.23	65.82

Pythia v1.0 [28]: Pythia v1.0 is the award winning architecture for VQA Challenge 2018¹. The architecture is similar to Teney et al. [14] with reduced computations with element-wise multiplication, use of GloVe vectors [23], and ensemble of 30 models.

Differential Networks [20]: This model uses the differences between forward propagation steps to reduce the noise and to learn the interdependency between features. Image features are extracted using Faster-RCNN [22]. The differential modules [30] are used to refine the features in both text and images. GRU [31] is used for question feature extraction. Finally, it is combined with an attention module to classify the answers. The Differential Networks architecture is illustrated in Fig. 4.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

The reported results for different methods over different datasets are summarized in Table I and Table II. It can be observed that VQA dataset is very commonly used by different methods to test the performance. Other datasets like Visual7W, Tally-QA and KVQA are also very challenging and recent datasets. It can be also seen that the Pythia v1.0 is one of the recent methods performing very well over VQA dataset. The Differential Network is the very recent method proposed for VQA task and shows very promising performance over different datasets.

As part of this survey, we also implemented different methods over different datasets and performed the experiments. We considered the following three models for our experiments, 1) the baseline Vanilla VQA model [1] which uses the VGG16 CNN architecture [3] and LSTMs [7], 2) the Stacked Attention Networks [12] architecture, and 3) the 2017 VQA challenge winner Teney et al. model [14]. We considered the widely adapted datasets such as standard VQA dataset [1] and Visual7W dataset [9] for the experiments. We used the Adam Optimizer for all models with Cross-Entropy loss function. Each model is trained for 100 epochs for each dataset.

The experimental results are presented in Table III in terms of the accuracy for three models over two datasets. In the experiments, we found that the Teney et al. [14] is the best

¹<https://github.com/facebookresearch/pythia>

performing model on both VQA and Visual7W Dataset. The accuracies obtained over the Teney et al. model are 67.23% and 65.82% over VQA and Visual7W datasets for the open-ended question-answering task, respectively. The above results re-affirmed that the Teney et al. model is the best performing model till 2018 which has been pushed by Pythia v1.0 [13], recently, where they have utilized the same model with more layers to boost the performance.

V. CONCLUSION

The Visual Question Answering has recently witnessed a great interest and development by the group of researchers and scientists from all around the world. The recent trends are observed in the area of developing more and more real life looking datasets by incorporating the real world type questions and answers. The recent trends are also seen in the area of development of sophisticated deep learning models by better utilizing the visual cues as well as textual cues by different means. The performance of even best model is still lagging and around 60-70% only. Thus, it is still an open problem to develop better deep learning models as well as more challenging datasets for VQA. Different strategies like object level details, segmentation masks, deeper models, sentiment of the question, etc. can be considered to develop the next generation VQA models.

REFERENCES

- [1] S. Antol, A. Agrawal, J. Lu, M. Mitchell, D. Batra, C. Lawrence Zitnick, and D. Parikh, "Vqa: Visual question answering," in *IEEE ICCV*, 2015, pp. 2425–2433.
- [2] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," in *NIPS*, 2012, pp. 1097–1105.
- [3] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," *arXiv preprint arXiv:1409.1556*, 2014.
- [4] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, "Rethinking the inception architecture for computer vision," in *IEEE CVPR*, 2016, pp. 2818–2826.
- [5] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *IEEE CVPR*, 2016, pp. 770–778.
- [6] L. R. Medsker and L. Jain, "Recurrent neural networks," *Design and Applications*, vol. 5, 2001.
- [7] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural computation*, vol. 9, no. 8, pp. 1735–1780, 1997.
- [8] M. Malinowski and M. Fritz, "A multi-world approach to question answering about real-world scenes based on uncertain input," in *NIPS*, 2014, pp. 1682–1690.
- [9] Y. Zhu, O. Groth, M. Bernstein, and L. Fei-Fei, "Visual7w: Grounded question answering in images," in *IEEE CVPR*, 2016, pp. 4995–5004.
- [10] M. Acharya, K. Kafle, and C. Kanan, "Tallyqa: Answering complex counting questions," *arXiv preprint arXiv:1810.12440*, 2018.
- [11] S. Shah, A. Mishra, N. Yadati, and P. P. Talukdar, "Kvqa: Knowledge-aware visual question answering," in *AAAI*, 2019.
- [12] Z. Yang, X. He, J. Gao, L. Deng, and A. Smola, "Stacked attention networks for image question answering," in *IEEE CVPR*, 2016, pp. 21–29.
- [13] Y. Jiang, V. Natarajan, X. Chen, M. Rohrbach, D. Batra, and D. Parikh, "Pythia v0.1: the winning entry to the vqa challenge 2018," *arXiv preprint arXiv:1807.09956*, 2018.
- [14] D. Teney, P. Anderson, X. He, and A. van den Hengel, "Tips and tricks for visual question answering: Learnings from the 2017 challenge," in *IEEE CVPR*, 2018, pp. 4223–4232.
- [15] S. Gupta, P. Arbelaez, and J. Malik, "Perceptual organization and recognition of indoor scenes from rgb-d images," in *IEEE CVPR*, 2013, pp. 564–571.
- [16] L. Yu, E. Park, A. C. Berg, and T. L. Berg, "Visual madlibs: Fill in the blank description generation and question answering," in *IEEE ICCV*, 2015, pp. 2461–2469.
- [17] J. Johnson, B. Hariharan, L. van der Maaten, L. Fei-Fei, C. Lawrence Zitnick, and R. Girshick, "Clevr: A diagnostic dataset for compositional language and elementary visual reasoning," in *IEEE CVPR*, 2017, pp. 2901–2910.
- [18] N. Silberman, D. Hoiem, P. Kohli, and R. Fergus, "Indoor segmentation and support inference from rgb-d images," in *ECCV*, 2012, pp. 746–760.
- [19] T.-Y. Lin, M. Maire, S. Belongie, J. Hays, P. Perona, D. Ramanan, P. Dollár, and C. L. Zitnick, "Microsoft coco: Common objects in context," in *ECCV*, 2014, pp. 740–755.
- [20] C. Wu, J. Liu, X. Wang, and R. Li, "Differential networks for visual question answering," *AAAI* 2019, 2019.
- [21] M. Ren, R. Kiros, and R. Zemel, "Exploring models and data for image question answering," in *Advances in neural information processing systems*, 2015, pp. 2953–2961.
- [22] S. Ren, K. He, R. Girshick, and J. Sun, "Faster r-cnn: Towards real-time object detection with region proposal networks," in *NIPS*, 2015, pp. 91–99.
- [23] J. Pennington, R. Socher, and C. Manning, "Glove: Global vectors for word representation," in *EMNLP*, 2014, pp. 1532–1543.
- [24] K. Yi, J. Wu, C. Gan, A. Torralba, P. Kohli, and J. Tenenbaum, "Neural-symbolic vqa: Disentangling reasoning from vision and language understanding," in *NIPS*, 2018, pp. 1031–1042.
- [25] J. Liang, L. Jiang, L. Cao, L.-J. Li, and A. G. Hauptmann, "Focal visual-text attention for visual question answering," in *IEEE CVPR*, 2018, pp. 6135–6143.
- [26] L. Jiang, J. Liang, L. Cao, Y. Kalantidis, S. Farfadi, and A. Hauptmann, "Memexqa: Visual memex question answering," *arXiv preprint arXiv:1708.01336*, 2017.
- [27] M. Tapaswi, Y. Zhu, R. Stiefelhagen, A. Torralba, R. Urtasun, and S. Fidler, "Movieqa: Understanding stories in movies through question-answering," in *IEEE CVPR*, 2016, pp. 4631–4640.
- [28] Y. Jiang, V. Natarajan, X. Chen, M. Rohrbach, D. Batra, and D. Parikh, "Pythia v0.1: the winning entry to the vqa challenge 2018," *arXiv preprint arXiv:1807.09956*, 2018.
- [29] K. Kafle and C. Kanan, "An analysis of visual question answering algorithms," in *ICCV*, 2017.
- [30] B. Patro and V. P. Namboodiri, "Differential attention for visual question answering," in *IEEE CVPR*, 2018, pp. 7680–7688.
- [31] J. Chung, C. Gulcehre, K. Cho, and Y. Bengio, "Empirical evaluation of gated recurrent neural networks on sequence modeling," *arXiv preprint arXiv:1412.3555*, 2014.