

# Document Visual Question Answering Challenge 2020

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**Abstract.** This paper presents results of Document Visual Question Answering Challenge organized as part of “Text and Documents in the Deep Learning Era” workshop, in CVPR 2020. The challenge introduces a new problem - Visual Question Answering on document images. The challenge comprised two tasks. The first task concerns with asking questions on a single document image. On the other hand, the second task is set as a retrieval task where the question is posed over a collection of images. For the task 1 a new dataset is introduced comprising 50,000 questions-answer(s) pairs defined over 12,767 document images. For task 2 another dataset has been created comprising 20 questions over 14,362 document images which share the same document template.

**Keywords:** visual question answering · document understanding

## 1 Introduction

Visual Question Answering (VQA) has attracted an intense research effort over the past few years, as one of the most important tasks at the frontier between vision and language. Notably, at the same time as reading systems research considered that the field of scene text understanding was mature enough to build scene text based VQA systems on, VQA researchers realised that the capacity of reading is actually important for any VQA agent. As a result, ST-VQA [2] and TextVQA [6] were introduced in parallel in 2019. In this year’s Visual Question Answering workshop at CVPR 2020, three out of the five VQA challenges actually revolve around text [3, 4]. The time seemed right for the introduction of a large scale scanned Document VQA task.

In this short paper we introduce the DocVQA dataset and the challenge organized as part of the “Text and Documents in the Deep Learning Era” workshop at CVPR 2020. The paper offers a quick description of the dataset, the challenge and results of the submitted methods to date. The challenge is open for continuous submission at the Robust Reading Competition (RRC) portal <sup>4</sup>.

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<sup>4</sup> <https://rrc.cvc.uab.es/?ch=17>

UNIVERSITY OF CALIFORNIA, SAN DIEGO

To: *PS*

Date: *2/25/00* Time: *4:00* A.M. P.M.

WHILE YOU WERE OUT

Dr. *Michael Gold*

Mr. *Science 80 Magazine*

Ms. *Science 80 Magazine*

From: *Science 80 Magazine*

☒ Telephoned ☐ Will phone again ☒ Please phone

☐ Came to see you ☐ Will come again ☐ Rush

MESSAGE

*Re: Stay Re. Bill*

*Walton*

*Telephone No. for Bill*

*Vanderburgh*

*202-232-0959 4:00pm*

Phone party at *(202) 967-5200*

Taken by *(over) P.D. -5209*

71475-0000 <https://www.industrydocuments.ucsf.edu/docs/liv0226>

PUBLIC DISCLOSURE COMMISSION  
111 CAPITOL WAY RM 200  
SACRAMENTO, CA 95833-0000  
PHONE 1-800-555-1111  
FAX 1-877-401-2228

Candidate Registration **C1**  
(1000)

Candidate's Name (Give candidate's full name.) *Callahan Campbell McKey*

Candidate's Committee Name (Do not abbreviate.)

Mailing Address *7014 Heggenes Island 98236*

City *Clinton* County *Denton* Zip + 4 *3*

1. What office are you running for? *Port Com Dis. 3* Legislative District, County or City

2. Political party (if partisan office)

3. Date of general or special election

4. How much do you plan to spend during your entire election campaign, including the primary and general elections? *0* See the reporting options below. If no box is checked you are obligated to use Option I, Full Reporting. See instruction manuals and changing reporting options.

☒ Option I **MINI REPORTING:** In addition to my filing fee of \$ *0*, I will raise and spend no more than \$5,000. Include and local voters pamphlet. I will not accept more than \$500 in the aggregate from any contributor except myself.

☐ Option II **FULL REPORTING:** I will use the Full Reporting system. I will file the frequent, detailed campaign reports required by WAC 380-05-243 and next page for details. List deputy treasurers on attached sheet.

5. Treasurer's Name and Address. Does treasurer perform only ministerial functions? Yes ☒ No ☐ See WAC 380-05-243 and next page for details. List deputy treasurers on attached sheet.

*Charles A. Glass 7323 Heggenes Rd 98236 Clinton WA*

6. Persons who perform only ministerial functions on your behalf add on behalf of other candidates or political committees. List name, title, address, phone number and next page for details.

*Charles A. Glass, Analyst, 7323 Heggenes Rd Clinton WA 98236*

Who is the message for ?  
What is the date of the message ?

In which legislative counties did Gary L. Schoessler run for County Commissioner?

Fig. 1: **(Left)** A sample document image and questions defined on it from the dataset for task 1. **(Right)** A sample document image from dataset for task 2 and a sample question posed on the whole task 2 document collection.

## 2 Challenge

The challenge ran between March and May 2020. Ranking of submitted methods presented in this report reflect state of submissions at the closure of the official challenge period.

The challenge comprised two separate tasks.

### 2.1 Task 1 - VQA on Document Images

Task 1 of the challenge is similar to the typical VQA setting, i.e. answer a question asked on an image; here a document image. Answer to the question is always text present in the image, or in other words it is an extractive QA task. The participants are required to submit their results on the test split of the dataset which comprise of 5188 questions defined on 1287 document images. For evaluation of the submissions, we use the same metric as ST-VQA challenge [1], which is Average Normalized Levenshtein Similarity (ANLS).

### 2.2 Task 2 - VQA on Document Image Collection

In task 2 the question is posed over a collection of documents instead of a single image. Hence, the task requires one to retrieve the evidence as well output the

answer. For this first edition, we focused on the first part to rank the methods, and left the second as an optional response, which is nevertheless evaluated. Performance of the methods for the retrieval part is scored by the Mean Average Precision (MAP), which is the standard metric in retrieval scenarios. It is important to note that we force positive evidences that have been equally scored by the methods, to be at the end of the ranking among those documents. This is to ensure that the ranking is consistent and do not depend on the default order, or the way the score is evaluated. Finally, in spite of the fact that answers score is not used to rank the methods, precision and recall are used to show the performance of the methods in this task.

### 3 Datasets

Dataset for task 1 [5] comprises 50,000 questions over 12,767 document images. The images are pages extracted from 6071 scanned documents sourced from the industry documents library<sup>5</sup>. We manually selected the documents from the library to ensure document variety. Each question-answer(s) pair in the dataset is also qualified with a question type among 9 types that denote the type of analysis required to arrive at the answer. The 9 question types are figure, ‘form’, ‘table/list’, ‘layout’, ‘running text’, ‘photograph’, ‘handwritten’, ‘yes/no’ and ‘other’. We also provide commercial OCR transcriptions of all the documents.

Dataset for task 2 consists of 14,362 document images sharing the same document template — US Candidate Registration form. Among these images there are documents filled in handwriting like Figure 1 (right), while others are typewritten. The images were sourced from the Open Data portal of the Public Disclosure Commission (PDC) and over this collection a set of 20 different questions is posed.

### 4 Results

**Task 1:** We received submissions from 9 different teams for task 1. The final ranking is shown in Table 1. Performance for the 9 submissions for different question types is shown in Figure 2.

**Task 2:** We received submissions from two different teams. The winning method is DQA from PingAn team, followed by a small margin by DOOCR from iFLYTEK team (see Table 2). None of the submitted methods provided the answers to the questions.

### 5 Acknowledgements

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<sup>5</sup> <https://www.industrydocuments.ucsf.edu/>

Method	ANLS
PingAn-OneConnect-	0.85
Gammalab-DQA	
Structural LM- v2	0.75
QA_Base_MRC.1	0.74
HyperDQA_V4	0.69
bert fulldata fintuned	0.59
Plain BERT QA	0.35
HDNet	0.34
CLOVA OCR	0.33
docVQAQV_V0.1	0.30

Table 1: Final ranking for task 1

Method	Retrieval MAP	Answers	
		Precision	Recall
DQA	0.8090	-	-
DOCR	0.7915	-	-

Table 2: Final ranking for task 2.

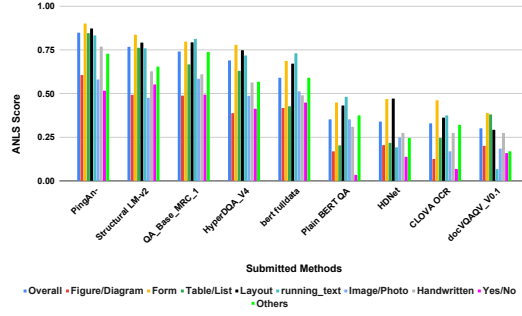


Fig. 2: Performance of the submitted methods for different question types in task 1.

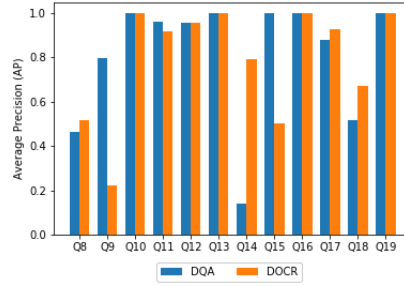


Fig. 3: Average precision of the submitted methods for each question in the test set.

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