Continual VQA for Disaster Response Systems



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- Solution 1: Don't use labels! Zero-shot VQA
- Solution 2: Train your model continually as labels are generated <u>Continual VQA</u>



Types of tasks

- 1. Classification
- 2. Segmentation
- 3. VQA



Image Class: Non-Flooded



Image Class: Flooded

Types of tasks

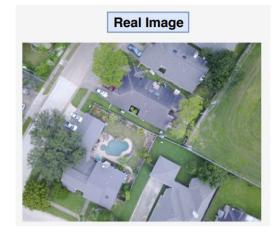
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QA Pair

What is the overall condition of the given image? Non-Flooded

How many buildings are non flooded? 6

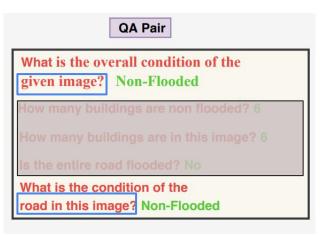
How many buildings are in this image? 6

Is the entire road flooded? No

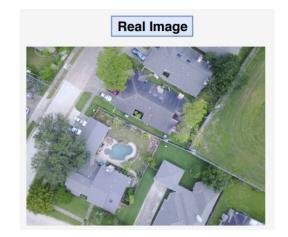
What is the condition of the road in this image? Non-Flooded

- 1. Condition Recognition
 - 1.1. Image Condition
 - 1.2. Road Condition
- 2. Yes/No
- 3. Counting Problem
 - 3.1. Simple Count
 - 3.2. Complex Count





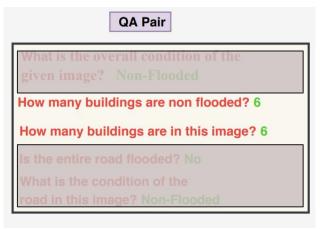
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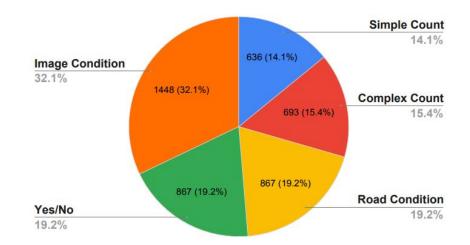


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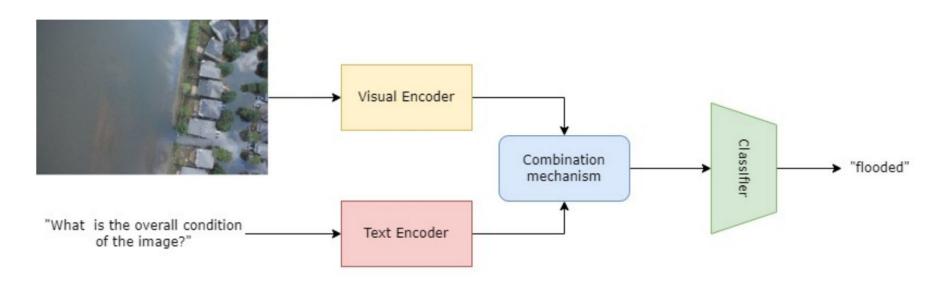




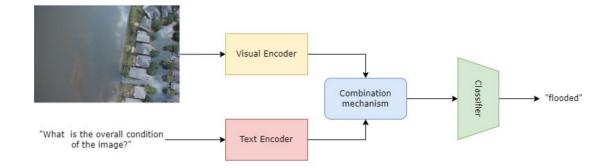
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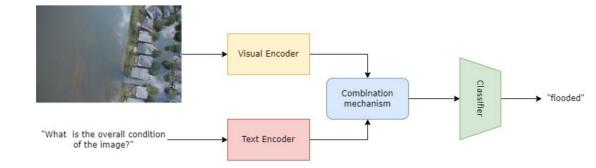
VQA Pipeline



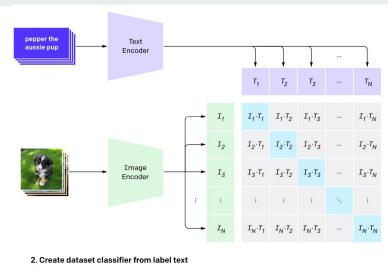
- Zero-shot VQA system
 - Multi-modal pre-trained models
- Continual VQA system
 - Trained on continuous stream of data

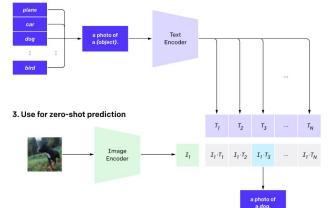


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 - 2. CLIP features for supervised training
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Results

Zero-shot VQA system

- 1. CLIP out-of-the-box
- 2. CLIP features for supervised training

Method	Taskwise Accuracy				
	Overall	Yes/No	Image Condition	Road Condition	
CNX-mul	98.03	98.31	98.62	97.18	

Kane and Khose (2022)

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CLIP out-of-the-box (ZS)

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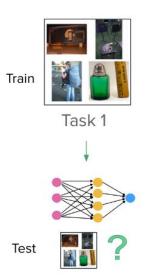
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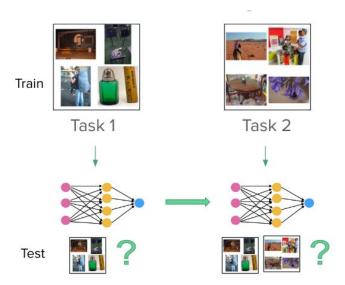
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CLIP out-of-the-box (ZS)

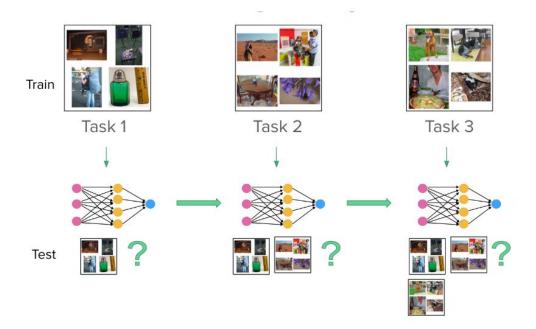
CLIP supervised (Best)

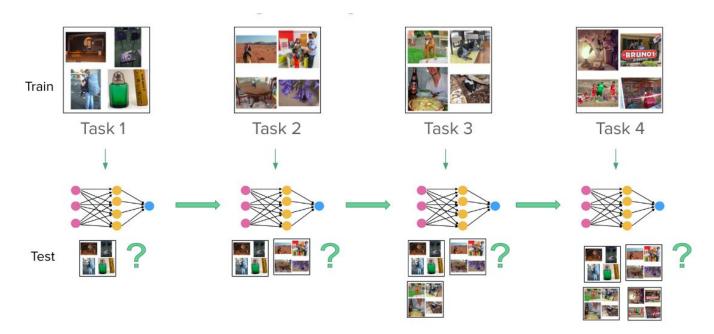
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CLIP-add	93.99	88.37	95.17	97.67	
CLIP-cat	92.97	81.97	95.86	97.06	
CLIP-mul	96.4	97.71	95.17	97.14	
CLIP-mul-taskwise	98.33	98.85	98.43	97.71	

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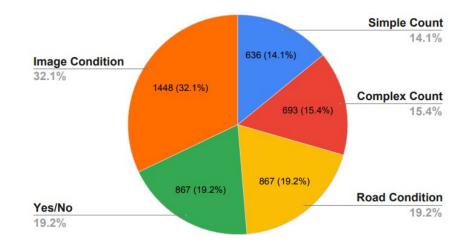






Our Tasks for Continual VQA

- 1. Task 1: Image Condition
- 2. Task 2: Road Condition
- 3. Task 3: Yes/No



Experience replay methods used

- 1. Reservoir Sampling Update
- 2. Ring Buffer
- 3. Mean of features



(a) Reservoir Sampling Update

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(b) Ring Buffer

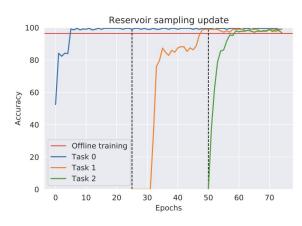
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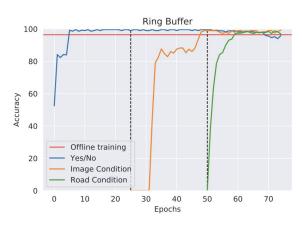
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(c) Mean of Features

CL Results







(a) Reservoir Sampling Update

(b) Ring Buffer

(c) Mean of Features

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- CLIP features for supervised training outperforms state-of-the-art on FloodNet VQA
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Thank you!

Feel free to reach us out in case of any questions



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Check out our paper and code!

- Paper: <u>arxiv.org/abs/2209.10320</u>