Supplementary material to:

On the Value of Out-of-Distribution Testing: An Example of Goodhart's Law

A Implementation details

A.1 Implementation of the proposed methods

The **random predictions, inverted** model discard the answers observed in the training set below a fixed threshold, so as to avoid the inverse operation to assign extremely large probabilities to them. The answers retained after thresholding are: yes, no, 1, 2, 3, and 1,100 *other* answers. The **random-image regularizer** is applied on a BUTD model pretrained with the standard BCE loss for 25 epochs. Our methods based on the BUTD model use standard implementation and hyperparameters [40]. The BUTD model is optimized for maximum likelihood over the training set $\mathcal{T}$ with a standard binary cross-entropy (BCE) loss and a logistic function over the the logits $\boldsymbol{a}^{\text{pred}} = f(\boldsymbol{q}, \boldsymbol{v})$:

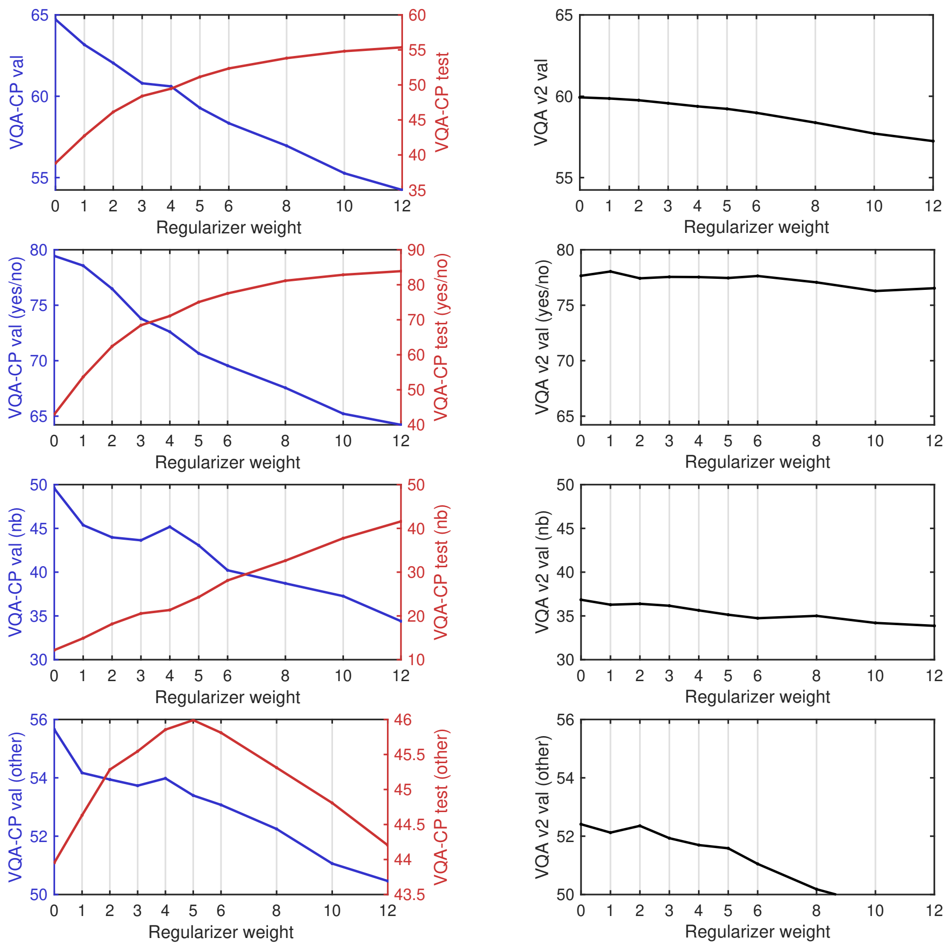
$$\mathcal{L}_{\text{BCE}}\left(\boldsymbol{a}^{\text{pred}}, \boldsymbol{a}^{\text{gt}}\right) \;=\; -\,\boldsymbol{a}^{\text{gt}} \log\left(\sigma(\boldsymbol{a}^{\text{pred}})\right) \;-\; \left(1 - \boldsymbol{a}^{\text{gt}}\right) \log\left(1 - \sigma(\boldsymbol{a}^{\text{pred}})\right)\,. \tag{3}$$

A.2 Experimental setup

Our experiments follow the (flawed) common practice of training each model on VQA-CP (the *v2* version) then on VQA v2. We report performance at the epoch of highest accuracy on VQA-CP test or VQA v2 validation respectively. In addition, when training on VQA-CP, we hold out 8,000 instances from the training set that measure in-domain performance following [41, 14]. For existing methods, we report the results of highest overall accuracy on VQA-CP test reported by their respective authors.

B Additional results

See next page.



(a) Model trained on VQA-CP.

(b) Model trained on VQA v2.

Figure 5: Performance of the random-image regularizer as a function of the regularizer weight (λ) for (top to bottom): all questions, questions with *yes/no* answers, *number* answers, and *other* answers.

Table 3: Accuracy of methods trained and evaluated on VQA-CP 'Other' questions alone. Existing methods were implemented on top of different baseline models, so we report the accuracy of both the baseline and the proposed versions.

Training set →	VQA-CP Training 'Other'	
Test set →	VQA-CP Val. 'Other'	VQA-CP Test 'Other'
Actively seeking [41]: baseline	45.46	31.09
Actively seeking [41]: as proposed	46.79 (+2.33)	34.25 (+3.16)
Gradient supervision [13]: baseline	54.74	43.33
Gradient supervision [13]: as proposed	**56.10** (+1.36)	44.70 (+1.40)
Unshuffling [14]: baseline	54.74	43.33
Unshuffling [14]: as proposed	53.98 (-0.76)	**48.06** (+4.73)
Random predictions	10.39	2.63
Random predictions, inverted	0.03	0.06
Learned baseline (BUTD)	**59.14**	45.96
Learned, top answer masked	22.68	22.87
Learned with random-image regularizer, λ=0 (=BUTD)	**59.14**	45.96
Learned with random-image regularizer, λ=1	58.19	46.60
Learned with random-image regularizer, λ=2	57.52	47.85
Learned with random-image regularizer, λ=3	57.60	47.79
Learned with random-image regularizer, λ=**4**	56.89 (-2.25)	**47.95** (+1.99)
Learned with random-image regularizer, λ=5	56.81	47.77
Learned with random-image regularizer, λ=6	56.27	47.52
Learned with random-image regularizer, λ=8	54.93	47.01
Learned with random-image regularizer, λ=10	54.07	46.72
Learned with random-image regularizer, λ=12	53.27	46.20

C Distribution of answers per question type in VQA v2 and VQA-CP

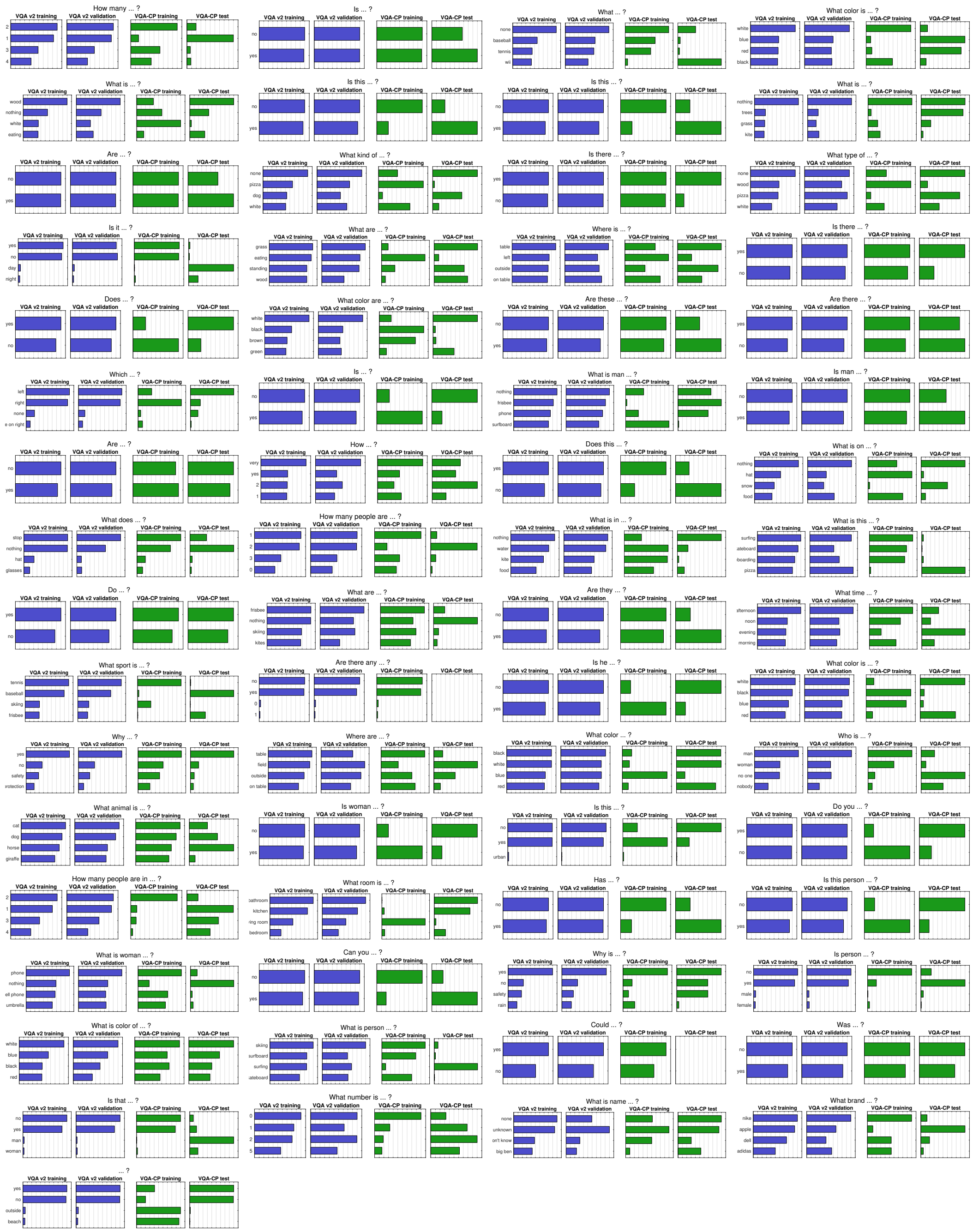


Figure 6: Histograms of the ten most frequent answers for every question prefix in VQA v2 and VQA-CP. The last prefix is empty and is the "catch all" default. Stop words are omitted in the figure, making some prefixes appear identical, *e.g. What is* and *What is the*. Best viewed electronically with magnification.