Supplementary Materials for VisualHow: Multimodal Problem Solving

Jinhui Yang^{*} Xianyu Chen^{*} Ming Jiang Shi Chen Louis Wang Qi Zhao University of Minnesota

{yang7004, chen6582, mjiang, chen4595, wangx723}@umn.edu, qzhao@cs.umn.edu

1. Introduction

The main text has introduced VisualHow – a free-form and open-ended research that focuses on understanding real-life problems and deriving solutions by integrating information over multiple modalities. The supplementary materials support our main findings with further evidence and report additional details of the VisualHow dataset and baseline models:

- Sec. 2 presents more detailed analyses and visualizations of our VisualHow dataset;
- (2) Sec. 3 presents the Amazon Mechanical Turk (AMT) interface for annotating the VisualHow dataset.
- (3) Sec. 4 presents the implementation details of all baseline models used in the experiments.

2. Dataset Visualizations

In this section, we present example problems and solutions, visualizations of problem categories, as well as the distribution of word tokens in the VisualHow dataset.

2.1. Data Examples

Fig. 1 shows the extended examples (see Fig. 2 of our main paper) with complete solutions. For illustration purpose, all of the presented examples have four solution steps. The image and caption of each step are shown along with their corresponding attention annotations. As shown in these examples, our dataset consists of a variety of attention annotations, such as objects (e.g., mice, food, water, dog, protective gloves, algaecide), abstract concepts (e.g., "sit" command, social skill words, healthy social behavior), and actions (e.g., take, give, reward, wear, role play). The corresponding visual attention (image regions) and textual attention (highlighted phrases) share the same color. For example, in Fig. 1b, the dog in the images is associated with the word "dog" in the captions. It is noteworthy that the dependencies between different steps form the solution graph, which is unique for each example. As shown in Fig. 1a,

to "care for pet during vacation", step 1 must completed first, because all the following steps depend on the decision made in step 1. However, steps 2-4 do not depend on each other. Differently, in Fig. 1b, all steps must be completed following a sequential order. These examples demonstrate the diverse annotations of solution graphs that enable the understanding of different types of solutions.

2.2. Categorical Analyses

Fig. 2 shows the number of subcategories in each category, ordered by the number of samples in each category. We find that higher number of samples per category does not necessarily indicate more subcategories. For example, Health has the highest number of subcategories, followed by Pets and Animals, while Sports and Fitness has the least. The different amount of subcategories reflects the original distribution of the wikiHow knowledge base.

2.3. Word Distributions

Fig. 3 presents the word distributions for frequent tokens used in the the VisualHow problems, solutions, and textual annotations. It shows the overall distributions as word clouds (first row), while highlighting the top-20 most frequent tokens (second row) and the distribution of (nouns, verbs, and other POS (parts of speech)). We find that all three types of text data share a similar distribution of nouns, verbs, and other types of POS, with slightly more nouns in the annotation text as well as less amount of other POS types. It is also noteworthy that although nouns are almost twice as many as verbs, a majority of the top-20 most frequent words are verbs. It suggests that both actions and objects are important for understanding and solving problems.

3. AMT Interface

Fig. 4 presents the complete AMT (Amazon Mechanical Turk) interface for the data annotation. Given a wikiHow problem, we first ask the crowd to annotate multimodal attention in the images and captions. These annotations include 1) important words with a corresponding region in

^{*}Equal contributions.

the image, 2) important words without any image correspondence, and 3) important image regions without corresponding words in the caption. The workers then review the multimodal attention annotations. The full solution graph is annotated by selecting dependencies of each step. In addition, they review the images and annotate the image types, and finally provide their feedback.

4. Experimental Details

In this section, we briefly describe the implementation details of our baseline models. Without loss of generalization, for each modality, *e.g.*, vision or language, we use v_1, \dots, v_K as the grid features from the ResNet [4] or the language features from the transformer [3], where *K* is the number of features. Each feature is represented as $v_i \in \mathbb{R}^V$, where *V* is the feature dimension. In the following context, we will use superscripts to represent the different sources of the extracted feature. More specifically, v_k^i , v_k^c and v_k^g represent the *k*-th grid feature of the image, the *k*-th language feature of the caption and the problem description, respectively.

GAP. For the global average pooling baseline, it computes the aggregated feature \hat{v}^i by calculating the average feature of each modality as follows:

$$\hat{\boldsymbol{v}}^{i} = \frac{1}{K} \sum_{k=1}^{K} \boldsymbol{v}_{k}^{i}, \qquad (1)$$

$$\hat{\boldsymbol{v}}^{c} = \frac{1}{K} \sum_{k=1}^{K} \boldsymbol{v}_{k}^{c}, \qquad (2)$$

$$\hat{\boldsymbol{v}}^{\boldsymbol{g}} = \frac{1}{K} \sum_{k=1}^{K} \boldsymbol{v}_k^{\boldsymbol{g}},\tag{3}$$

where \hat{v}^i , \hat{v}^c and \hat{v}^g are the aggregated image features, caption features and problem features, respectively.

GPO. For the generalized pooling operation baseline, we follow the method of [2] (see Sec. 3.2 and Sec. 3.3) to compute the aggregated features \hat{v}^i , \hat{v}^c and \hat{v}^g for image, caption and problem description, respectively.

ATT. The baseline with an attention mechanism is implemented following the Bottom-Up and Top-Down image captioning model [1]. Specifically, we compute a weight vector a_k^i for each of the K image features v_k^i as follows:

$$a_k^i = \boldsymbol{w}_{ai}^T \tanh(W_{ai}\boldsymbol{v}_k^i + W_{gi}\boldsymbol{v}_k^g), \qquad (4)$$

where $W_{ai} \in \mathbb{R}^{H \times V}$, $W_{gi} \in \mathbb{R}^{H \times V}$ and $\boldsymbol{w}_{ai} \in \mathbb{R}^{H}$ are learned parameters, and H is the dimension of the projection layer.

Similarly, the attention weights a_k^c for each of the K language features v_k^c in the solution description and a_k^g for each of the K language features v_k^g in the problem description are computed as

$$a_k^c = \boldsymbol{w}_{ac}^T \tanh(W_{gc} \boldsymbol{v}_k^g + W_{cc} \boldsymbol{v}_k^c), \qquad (5)$$

and

$$a_k^g = \boldsymbol{w}_{ag}^T \tanh(W_{ag} \boldsymbol{v}_k^i + W_{gg} \boldsymbol{v}_k^g + W_{cg} \boldsymbol{v}_k^c), \quad (6)$$

where $W_{gc} \in \mathbb{R}^{H \times V}$, $W_{cc} \in \mathbb{R}^{H \times V}$, $W_{ag} \in \mathbb{R}^{H \times V}$, $W_{gg} \in \mathbb{R}^{H \times V}$, $W_{cg} \in \mathbb{R}^{H \times V}$, $\boldsymbol{w}_{ac} \in \mathbb{R}^{H}$ and $\boldsymbol{w}_{ag} \in \mathbb{R}^{H}$ are the learned parameters. For simplicity, in solution steps prediction task, we do not consider \boldsymbol{v}_{k}^{i} and \boldsymbol{v}_{k}^{c} to get a_{k}^{g} .

Finally, we normalize the attention weights a_k^i , a_k^c , a_k^g using a softmax function, and apply them to the corresponding features.

$$\hat{\boldsymbol{v}}^m = \sum_{k=1}^K \operatorname{softmax}(\boldsymbol{a}_k^m) \boldsymbol{v}_k^m, \tag{7}$$

where m indicates the corresponding modality, *i.e.*, image (i), caption (c) or problem description (g).

References

- [1] Peter Anderson, Xiaodong He, Chris Buehler, Damien Teney, Mark Johnson, Stephen Gould, and Lei Zhang. Bottom-up and top-down attention for image captioning and visual question answering. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2018.
- [2] Jiacheng Chen, Hexiang Hu, Hao Wu, Yuning Jiang, and Changhu Wang. Learning the best pooling strategy for visual semantic embedding. In *Proceedings of the IEEE Conference* on Computer Vision and Pattern Recognition (CVPR), 2021.
- [3] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: Pre-training of deep bidirectional transformers for language understanding. In North American Chapter of the Association for Computational Linguistics (NAACL), 2019.
- [4] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016.

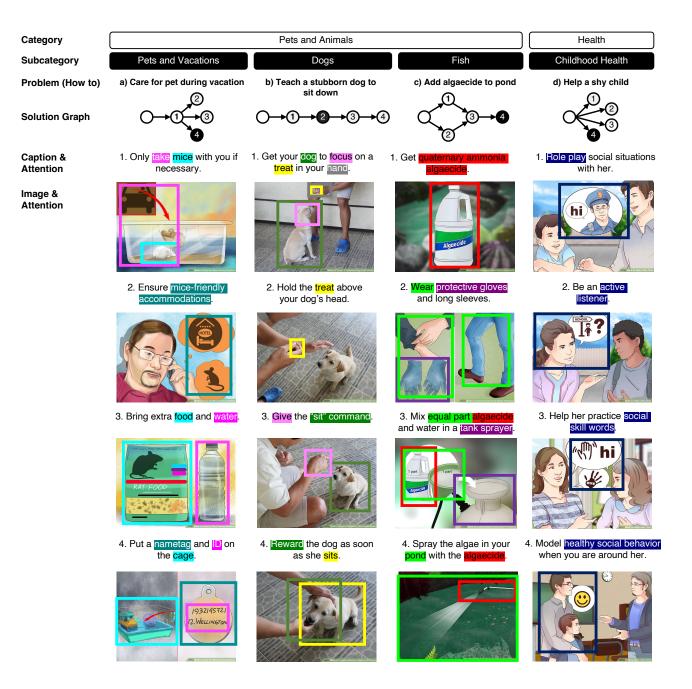


Figure 1. An overview of the VisualHow dataset. We provide a hierarchical structure that organizes our data into categories, sub-categories, problems, solution graphs, steps with image-caption pairs, and multimodal attention.

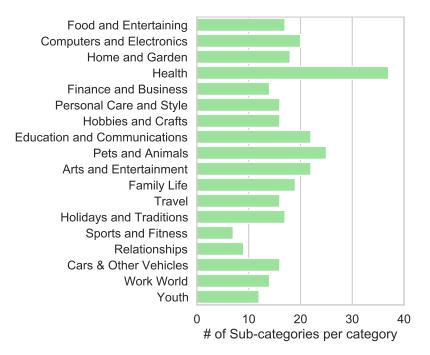


Figure 2. Numbers of subcategories in each category.

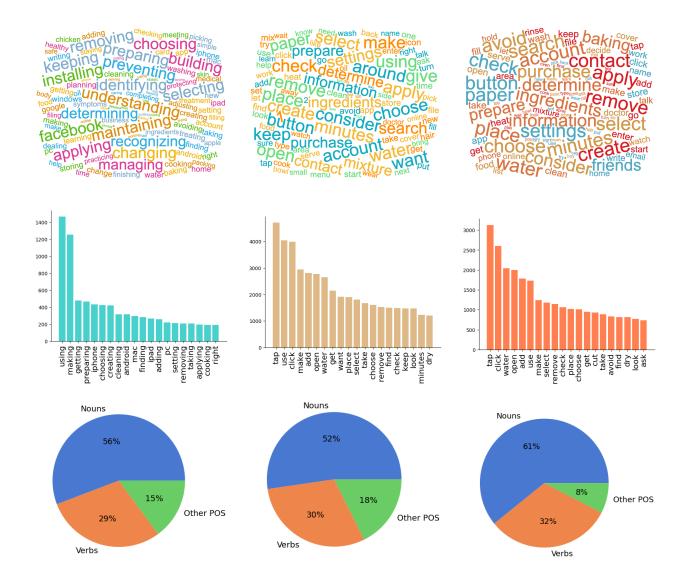


Figure 3. Distribution of words in problem descriptions (column 1), solution descriptions (column 2) and annotations (column 3). Top row: word clouds for frequent words. Middle row: distributions of the top-20 most frequent words. Bottom row: distributions of parts of speech.

(a) wikiHow Article



(b) Multimodal Attention

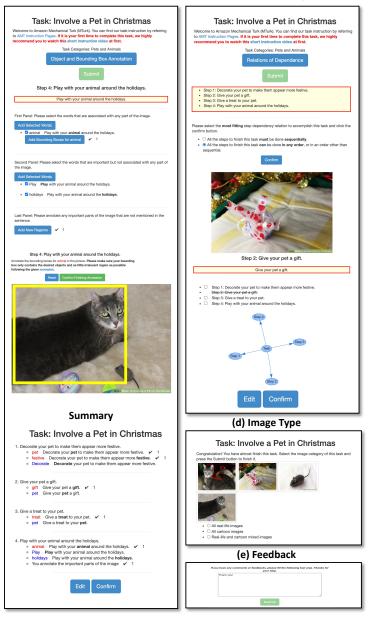


Figure 4. Crowdsourcing interface of the VisualHow task, which contains a) an overview of the wikiHow article, b) annotation of the multimodal attention, and c) annotation of the solution graph, d) annotation of image type, and e) feedback.