AssistQ: Affordance-centric Question-driven Task Completion for Egocentric Assistant (Supplementary Material)

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1 Dataset Quality Control

To ensure the quality of videos and scripts, we worked with participants closely (e.g. dissemination of comprehensive submission guidelines, checking of device before filming, hands-on recording guidance, review of transcripts). Researchers also conduct a quality check on the recorded videos before acceptance. In fact, 2-3% of videos have been rejected due to undesired quality (e.g. unclear video instructions). To ensure the quality of QA pairs and annotation, AssistQ also adopted all 4 quality control measures referenced in TGIF-QA [3]: gold standard annotation to help annotators to understand requirements, rejection and reviews (each video has been audited by at least 1 more person). The high quality of our data can be further confirmed by the high human performances at 95.8% recall@1.

2 Dataset Collection Source

We noticed that many virtual world simulators could help to produce a clean dataset, but we hold on collecting data in the real world. The main reason is that ultimately we want to deploy such AI assistant models in real environments such as smart glasses. To this end, at least we need to have testing data in real environment. Regarding training data, we agree it is a promising research direction to leverage a virtual environment. However, due to the significant domain gap between the existing virtual environments (e.g., AI2Thor [4], AI Habitat [7]) and the real env, real-world training data at the scale provided by us is needed to adapt model trained in virtual to real. In this paper’s scope, we focus on models trained only on the real environment; we consider it as future work to pre-train in the virtual environment first and then fine-tuning it on real-world data.

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3 Some Dataset Challenges

There are some interesting challenges in our dataset. These challenges are summarized in Figure 1. Some challenges include (a) changing views within the same instructional video; (b) occlusion of buttons due to hand placement, narrow views or hidden buttons; (c) faint buttons from lighting; (d) motion blurs from ego-motion or out-of-focus cameras; as well as; (e) user images taken under different angles and lighting from the video, reiterating the richness and complexity of AssistQ.

4 Dataset Comparison

Table 1 compares AssistQ to related datasets. As we can see, AssistQ is unique compared to others: (1) the video content is sourced from real-world, everyday situations in the egocentric perspective, (2) the question are affordance-centric i.e. how to use and execute functions of appliances, and multi-modal to more closely reflect the inputs that an AI assistant (e.g. AR glass) receives from the user. (3) Answers are a sequence of actions for the user to execute. AssistQ also has longer videos on average compared to most datasets.
### Dataset Comparison

| Dataset        | Video Source | Video Type   | Questions | Question Modality | Answers     | #Clips | #QA | Ave Dur (s) |
|----------------|--------------|--------------|-----------|-------------------|-------------|--------|----|-------------|
| MovieQA [8]    | Movie        | Third-person | Factoid   | ✓                 | -           | 408    | 14,944 | 202.7       |
| TVQA [5]       | TV show      | Third-person | Factoid   | ✓                 | -           | 21,793 | 152,545 | 76.2        |
| AVSD [1]       | Crowdsourced | Third-person | Factoid   | ✓                 | ✓           | 11,816 | 118,160 | 30          |
| Embodied QA    | Simulated env.| Egocentric  | Factoid   | ✓                 | ✓           | 5,281  | -     | -           |
| AssistQ (ours) | Crowdsourced | Egocentric  | Affordance | ✓                 | ✓           | 100    | 531   | 115         |

**Table 1.** Comparison of AssistQ with related datasets.

**MovieQA [8].** The goal of MovieQA is to understand story plots in movies. 408 subtitled movies were collected together with their Wikipedia synopsis and insdb/Described Video Service (DVS) scripts where available. In the first round of annotation, the annotators were shown the plot synopsis only and asked to create any number of QA pairs that can be localized to a set of sentences in the synopsis. Naturally, this led to questions that were plot-focused and less reliant on visual information. In the second round of annotation, annotators were asked to create 5 multiple-choice answers (1 right, 4 wrong) based on the synopsis and questions. Finally, each sentence of the synopsis was aligned to time-stamps on the video clips (∼200s in length); the video clip and aligned QA pairs then formed the benchmark (Figure 2).

**TVQA [5].** Similar to MovieQA, TVQA was created to understand human-centric plots in videos. 6 TV shows were segmented into 60/90-second clips, accompanied by subtitles and aligned transcripts. Annotators were shown the video clip and aligned subtitles, and encouraged to create questions in a 2-part format: [What/How/Where/Why/. . .] ______ [when/before/after] ______. The second part served to localize the question to the relevant moment in the clip and ground the question in visual signals, such as *What was House saying before he leaned over the bed?*. Annotators provided 5 multiple-choice answers (1 right, 4 wrong) and annotated time-stamps of the exact video portion required to answer the question (Figure 3).

**AVSD [1].** In Audio Visual Scene-Aware Dialog (AVSD), an agent is given an input video, a dialog history and a follow-up question, and its goal is to generate a correct response (Figure 4). 11,816 videos of everyday human activi-
Fig. 3. Examples from the TVQA dataset. The question had to be written with a [when/before/after] clause so that it is localized to a specific moment in the clip. 54% of questions were about what, followed by 15% about who.

Fig. 4. Examples from the AVSD dataset. The “Questioner” asks a series of questions about the input video and the “Answerer” gives an answer at each round.

**Embodied QA** [2]. In Embodied QA, an agent is spawned at a random location in a simulated home environment and asked a question about the colour/location of an object. The objective of the agent is to navigate the environment through atomic actions (move forward, turn, etc.) and gather visual information to answer the question (Figure 5). The dataset is built on a subset of House3D environments, and the questions were written in specific formats to ensure they were answerable and unambiguous. For example, location questions were written as *What room is the <OBJ> located in?*, where <OBJ> is an unambiguous object that is query-able.
5 Data Sample Visualisation

We attach an annotated example and an animated video to showcase the intended use-case of AssistQ in AI assistants. The video shows 2 examples with egocentric instructional videos, and an example with a third-person instructional video.

**Annotated example.** We provide 1 annotated example from AssistQ to illustrate the format and information encapsulated in our annotations. The example contains the instructional video (video.mp4), question-answering pairs (qa.json), bounding box coordinates (buttons.csv), narration transcript (script.txt) as well as the image folder containing front-view image(s) of the device.

**Examples with egocentric videos.** We showcase 2 examples from our AssistQ dataset, namely the [EF stove] and [Bosch washing machine] in an animated video (Figure 6). Through these examples, we demonstrate the use of AssistQ in our proposed Affordance-centric Question-driven Task Completion (AQTC) task. The AI assistant learns offline from an egocentric instructional video so that when the user asks a question (e.g. stove: How do I switch on the left stove at maximum heat), the AI assistant provides the user with a series of steps to perform (e.g. stove: 1. Press [here], 2. Press [here] and 3. Select [here] mode 9). Each step is grounded to bounding boxes in the user’s image, i.e. [here] refers to a labelled button/knob on the device. The bounding box is shown on the user’s view of the device (e.g. through AR glasses) so the user knows the exact action to perform.

**Example with third-person video.** In the animated video, we also include a [Shark vacuum] example that had its instructional video recorded in third-person (Figure 7). Compared to the egocentric examples, the third-person example is
Fig. 6. Illustration of AQTC task with an example from AssistQ. The AI assistant learns offline from a narrated instructional video. The user wonders how to use the appliance and shows the AI assistant their view. The AI assistant predicts the sequence of actions that the user should perform to accomplish the task, and guides the user through each step with bounding boxes over their view of the appliance.

more challenging as it requires the AI assistant to resolve visual information from the third-person video with that of the user’s egocentric visual query. The example demonstrates that the AQTC task need not be confined to egocentric videos. We intend to extend the AssistQ dataset to include more examples with third-person videos, as it is more common for product videos/demos to be recorded in third-person. This will allow further research and development in AI assistants to benefit from our AQTC task and AssistQ dataset.

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Fig. 7. Illustration of AQTC task with instructional video recorded from the third-person perspective. The task remains largely unchanged, except that the model has to resolve visual signals from the third-person to the first-person image from the user. This presents new challenges for the AQTC task and we are expanding the AssistQ dataset to include more of such scenarios.

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