Understanding Procedural Knowledge by Sequencing Multimodal Instructional Manuals

Te-Lin Wu¹, Alex Spangher², Pegah Alipoormolabashi³, Marjorie Freedman², Ralph Weischedel², Nanyun (Violet) Peng¹
¹University of California, Los Angeles, ²Information Sciences Institute, University of Southern California, ³Sharif University of Technology
{telinwu, violetpeng}@cs.ucla.edu, palipoor976@gmail.com {spangher, mrf, weischedel}@isi.edu

Abstract

The ability to sequence unordered events is an essential skill to comprehend and reason about real world task procedures, which often requires thorough understanding of temporal common sense and multimodal information, as these procedures are often communicated through a combination of texts and images. Such capability is essential for applications such as sequential task planning and multi-source instruction summarization. While humans are capable of reasoning about and sequencing unordered multimodal procedural instructions, whether current machine learning models have such essential capability is still an open question. In this work, we benchmark models’ capability of reasoning over and sequencing unordered multimodal instructions by curating datasets from popular online instructional manuals and collecting comprehensive human annotations. We find models not only perform significantly worse than humans but also seem incapable of efficiently utilizing the multimodal information. To improve machines’ performance on multimodal event sequencing, we propose sequentiality-aware pre-training techniques that exploit the sequential alignment properties of both texts and images, resulting in >5% significant improvements.

1 Introduction

Instructions are essential ways for agents to learn how to complete a complex task composed of multiple steps, such as “making a wood sign from scratch”. However, instructions may not always come in a proper sequential order, such as obtaining instructions for one task from multiple different sources. Therefore, sequencing unordered task steps is crucial for comprehending and inferring task procedures, which requires thorough understanding of event causal and temporal common sense. It is essential for applications such as multi-source instruction summarization and robot task planning (Garattoni and Birattari, 2018).

Figure 1: Multimodal task procedure sequencing: The left column shows a scrambled instruction steps from the manual How To Make Wood Signs. Each step is a text description and its associated image. Without the complementary information from the visuals, a novice may have difficulty inferring the proper task order. Considering multimodal information, the proper order can be correctly inferred (right column).

Existing works have studied sequencing unordered texts from paper abstracts or short stories (Chen et al., 2016; Cui et al., 2018). However, real-life tasks are often complex and multimodal information are often provided to supplement textual descriptions to avoid ambiguity or illustrate details that are hard to explain in pure language, as illustrated in Figure 1.

To investigate to which degree current AI techniques can sequence unordered task instruction steps and leverage multimodality to facilitate the reasoning, we consider online instructional manuals as the resource. We curate two representative instruction resources, cooking recipes and a “How-To” instructions (WikiHow); and establish human performance on a selected subset for each data resource. As certain instructions can potentially carry other possible step-orders alternatively to the original written ones, we additionally collect annotations of possible alternative orders to gauge the interchangeability of certain task-steps.

To benchmark the current models’ performance on the instructional action sequencing task, we construct models which consist of: (1) an input en-
coder which encodes images, texts, or multimodal inputs, and (2) an order decoder which predicts proper step order using the representation learned by the encoder. We employ RoBERTa (Liu et al., 2019) for the textual encoder, and the following two models: VisualBERT (Li et al., 2019) and CLIPViL (Shen et al., 2021), mainly differ by how the visual inputs are encoded, for multimodal encoders. To predict the step order, we integrate the encoders into a recent neural sentence ordering framework, BERSON (Cui et al., 2020).

To equip the multimodal models with awareness of sequentiality as well as a finer granularity of grounding between the textual and image contents, we propose the following pretraining objectives: (1) sequence-based multimodal masked language modeling (MLM), (2) image-swapping prediction (IS) which asks the models if some images are not following proper order in a sequence, (3) patch-based image-swapping prediction (P-IS) which is similar to IS but acts on the image-patch level, and (4) sequence-based masked region modeling (MRM) which requires the models to reconstruct masked image patches with a dynamically constructed visual vocabulary in the mini-batch training.

Extensive experiments show that for both standard and multi-reference versions of our task, multimodal information is consistently helpful, and our proposed pretraining techniques can further improve multimodal models’ performance. We conduct in-depth analysis to investigate different aspects of the sequencing task, specifically we incorporate the category information of WikiHow to provide insights on how humans and models perform, and investigate the interchangeability of certain task-orders along with evaluating models’ performance while considering alternative orders.

Our key contributions are three-fold: (1) We propose the multimodal sequencing task and curate a dataset from two instructional manuals, where we establish human performance as well as potential alternative orders to the instruction steps. (2) We investigate the model performance on sequencing an unordered manual, where we show multimodality is helpful and our proposed pretraining techniques further improve model performances, yet we find a significant gap (∼ 15%) between human and machine performances. (3) We conduct extensive analysis on our curated datasets as well as the model performance to provide more in-depth insights.

2 Problem Definition

Given a task procedure $S$ consisting of $N$ steps, where each step $S_i \in S$ can consist of two types of contents: a textual description $T_i = \{T_{i,1}, ..., T_{i,n}\}$ and/or image(s) $I_i = \{I_{i,1}, ..., I_{i,n}\}$. In this work, we restrict that $n = 1$ for the image contents, but our proposed framework can be seamlessly extended to take multiple images within a step. A model is then required to take as inputs a random permutation of $S$, i.e. $S_p = \{S_{p_1}, ..., S_{p_N}\}$, where $p$ is a permutation ($S_p$) can take one of the three following modalities: $T_{p_j}, I_{p_j}$, and $\{T_{p_j}, I_{p_j}\}$, and predict the correct order of $S_p$, i.e. $\text{argsort}(S_p)$.

3 Datasets and Human Annotations

3.1 Datasets

There are three major features we require from the target datasets: (1) It is multimodal. (2) It consists of task procedures as sequences of steps, where each modality shows clear procedural characteristics. (3) Different modalities are used intentionally to complement each other. In light of these, we consider the two following datasets:

3.1.1 RecipeQA

We start from a popular kind of procedural instruction manuals, recipes, which fully fulfill the aforementioned criteria. RecipeQA is a multimodal question answering dataset consists of numerous recipes scraped from Instructables.com (Yagcioglu et al., 2018). We utilize the recipes collected in this dataset as they are inherently procedural and multimodal. We utilize RecipeQA by converting each unique recipe into sequential multimodal steps for our sequencing task.

3.1.2 WikiHow

WikiHow is an online knowledge base that consists of human-created articles describing procedures to accomplish a desired task. Each article contains a high level goal of a task (e.g. “How To ...”), a short summary of the procedures introduced, and several multimodal steps where each step consists of a description paired with one or a few corresponding images and/or gifs. Prior work (Zhang et al., 2020b) also considers WikiHow for learning event temporal ordering, but with a limitation of only handling pairwise relative order. We are the first to consider WikiHow as a resource for a comprehensive multimodal procedural understanding.
We scrap the entire WikiHow knowledge base, containing more than 100k unique articles along with most of its multimodal contents\(^1\), as well as the hierarchical category (i.e. subcategory paths) for each article. For details, see Append. Sec. A.1.

### 3.2 Human Performance Benchmark

In order to ensure the validity of our proposed multimodal sequencing task, we establish the human performance via Amazon Mechanical Turk annotations. Since our benchmark dataset is constructed from resources that are not directly designed for our sequencing task, the quality of random samples is unverified, specifically in WikiHow, a number of articles may not have any notions of a proper order among the instructional steps (such an issue is much less severe in RecipeQA). As a result, to construct a high quality test set particularly for WikiHow, where our human annotation will be evaluated on, our internal members first select a set of categories which are hypothesized to be more likely to possess sequential tendency, e.g. Cars and Vehicles, Home and Garden, and Hobbies and Crafts. And then a random proportion is sampled where three members further downsample the subset to 300 samples with the aforementioned criteria: procedural in both texts and images and complementary multimodal information. The final proportion of samples are selected by majority vote and served as our golden-test-set for establishing human performance as well as evaluating the models. For RecipeQA, we randomly sample 100 samples from the dataset, which results in totally 400 samples for our golden evaluations.

Apart from the sequencing task, we also ask the annotators for their confidence of predictions and if multimodality is helpful for deciding the order. For more details, see Append. Sec. C.

### 3.3 Alternative Orders

In this work, we seek to examine the sequential understanding of models on instruction steps from the aforementioned manuals, however, we observe that it is not always true to enforce an only possibility of the step order. In real world, humans are capable of inferring of which steps there are possibilities of following an alternative ordering of such steps. To investigate this, we conduct another round of annotations\(^2\) where we ask the workers to list possible alternative orders to the original written ones. As the resulting agreement is sufficiently high (see Section 3.4 and Section 5.4), we retain the alternative orders which are majority agreed upon for each instance in our datasets.

### 3.4 Inter-Annotator Agreements (IAA)

#### Standard Performance

As orders concern not only positioning of the items but also more complicated relative information among the items, we propose to measure the agreements among orders centering around the concept of pairwise relationship. Specifically, we transform an integer sequence order to an one-hot encoded representation of the \(\binom{N}{2}\) pairs of relationships among the order. For example, suppose there are three items \(\{1, 2, 3\}\) to be ordered, where all the pairwise relations are \(\{12, 13, 21, 23, 31, 32\}\), then the one-hot pairwise relation representation of order \(123\) is \(R_{123} = \{12: 1, 13: 1, 21: 0, 23: 1, 31: 0, 32: 0\} = \{110100\}\), i.e. \(R_o(ij) = 1\) iff \(ij\) exists in the order \(o\). Similarly, \(R_{231} = \{001110\}\).

Using the aforementioned representation \(R_o\), we can compute Cohen’s Kappa inter-annotator agreement score for a pair of annotated order per each instance. The overall scores can be computed by firstly taking the average of pairwise Kappa scores of annotations for each instance, and then taking the average across the entire dataset. We report the IAAs in Section 5.3.

#### Alternative Orders

To evaluate the agreements for the additional annotated alternative orders, we focus on the differences of the transformed one-hot pairwise relation representations to the original ground truth order. We first compute the one-hot difference between an alternative order to the ground truth order, e.g. for three items, suppose ground truth order is simply \(123\), and an alternative order is \(o = 132\), then \(R_{diff}^{oi} = abs\{110100\} - \{110001\} = \{000101\}\). We apply the Kappa score for a pair of alternative orders by retaining the union of the positions where each alternative order differ from the ground truth in the one-hot representation, so as to focus on the agreements on differences to the original ground truth.

In order to compute the agreements of two series of alternative orders from two annotators (the series can have different lengths), we first exhaust the best matching pair (judged by the aforementioned Kappa scores) of orders drawn from the two series. When one annotator annotates more orders than

\(^1\)The dataset and relevant tools will be made public.

\(^2\)With different set of AMT workers than those participate in the standard human performance benchmark.
the other, the remaining orders (ones that were not included as any of the best matches) will be compared to the ground truth order to serve as the penalty. For a particular instance, we take the mean of all the Kappa scores (the best-matching-pair scores and the penalty scores) as the IAA for the two annotators. The overall IAA is computed similarly to the standard case, which we report in Section 5.4, with details in Appendix Sec. C.

4 Models

The model, which takes as inputs a set of unordered task-steps and predicts the appropriate order, is learned through the following procedures: (1) an encoder will take different modalities (i.e., multimodal or only the texts/images) of inputs and undergo our proposed sequentiality-aware pretraining, and then (2) an order decoder will utilize the representations produced by the sequence-pretrained encoder to predict the output orders.

4.1 Input Encoders

4.1.1 Text-Only Encoders

We use RoBERTa (Liu et al., 2019), an optimized variant of BERT language model (Devlin et al., 2019), for text-only inputs. Although one can claim that the next-sentence prediction in the original BERT model can be exploited for pairwise sequencing, we empirically find that RoBERTa, however not trained with such an objective, enjoys overall better performance than BERT.

4.1.2 Multimodal & Image-Only Encoders

We consider the following two variants of visual-linguistics (V&L) BERT-style models due to their simplicity of adapting to our sequencing task:

VisualBERT (Li et al., 2019) grounds detected image regions (extracted by vision object detectors such as Faster-RCNN (Ren et al., 2016)) to language with a single transformer model (Vaswani et al., 2017). VisualBERT is pretrained with: (1) multimodal masked language modeling (MLM), and (2) image-text matching prediction (ITM). In ITM, the image is randomly replaced with another one to create misalignment, and the model is required to predict whether the current image-text pair is aligned. Typically V&L models use image captioning (Chen et al., 2015) as training resource.

CLIP-ViL (Shen et al., 2021) is also a single-stream V&L model similar to VisualBERT, while the visual encoder is replaced by an image-patch-based model inspired by CLIP (Radford et al., 2021), where the image features are taken as gridded-image-patches instead of regional features proposed by object detectors (see Figure 2). The pretraining objectives remain the same as VisualBERT. Empirically, in both (Shen et al., 2021) and our work, we find such patch-based model yield better downstream performance, and hence we mainly base our multimodal encoder off CLIP-ViL.

Image-Only Models. We attempt to provide an image-only baseline on our sequencing task with two vision models: (1) ResNet-based (He et al., 2016) Faster-RCNN model (which is also the visual encoder in VisualBERT) where we utilize the proposed regional features as well as the whole-image-feature, and (2) the aforementioned patch-based CLIP model used in (Shen et al., 2021). Our empirical studies find that CLIP again show better performance on the image-only version of our task, consistent with the multimodal version.

4.2 Sequentiality-Aware Pretraining

The standard multimodal grounding (Li et al., 2019; Lu et al., 2019; Su et al., 2020; Chen et al., 2020a) does not explicitly concern sequentiality of text segments and image sequences, as these works often deal with single image-to-text grounding. In order to facilitate the downstream sequencing task, we propose pretraining objectives to equip models with awareness of sequentiality of input sequences, especially for sequential multimodal grounding. The pretraining objectives include the followings: (1) masked language modeling (MLM), (2) image-swapping predictions (IS), (3) patch-based image-swapping predictions (P-IS), and (4) sequential masked region modeling (MRM). Figure 2 illustrates an overview of the input sequence encoder and the pretraining paradigm. The proposed objectives can be applied to arbitrary length of input sequence, we hereby show two representative steps.

For these proposed objectives, the inputs to the models are generally a sequence following the original procedural order, however, the sequences can be sub-sampled to handle varying subsequences of the original procedures. Although we do not find this necessarily benefit the downstream perfor-

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3Bugliarello et al. (2020) suggests that many V&L models can achieve similar downstream performance if well trained.

4We use RoBERTa to initialize our version of VisualBERT.

5Without confusion, throughout the paper we term the CLIP-inspired visual encoder simply as CLIP.
mance, it is observed that the sub-sampling helps the model converge faster. Without loss of generality and for simplicity, the following sections assume the sub-sampled sequence is of length 2.

4.2.1 Masked Language Modeling (MLM)

The standard MLM (Devlin et al., 2019) is also employed for the text-only models, in order to adapt the pretrained language models to the task domain which may contain articles outside of the pretraining domains, such as crafting manuals or recipes. Following prior V&L works, we also adopt the MLM objective to facilitate the grounding. Particularly for the multimodal MLM, we ensure that the textual description of each step $T_i$ gets similar amount of maskings such that the models can potentially exploit the image sequences more.

4.2.2 Swapping-Based Prediction (IS/P-IS)

This objective concerns, with certain probability, randomly swapping a pair of items in a sequence and asking the model to judge whether the sequence is still properly ordered or not (i.e., binary classification). We mainly perform the swapping in the image modality and hence it can be viewed as an extended sequence-aware version of ITM objective in most V&L models. As in ITM, the output representation at the [CLS] token is used to make the prediction (with an MLP added on top).

**Standard.** For a correctly ordered sequence $S$, we can randomly swap two items of $S$, $\{S_i, S_j\}$, where $i < j$, to $\{S_j, S_i\}$, with a certain probability $\delta$. Our preliminary studies find that swapping the textual inputs do not necessarily help the downstream performance for either the text-only or multimodal models, so we do not apply this objective to the textual contents, and only perform the swapping on the images $\{I_i, I_j\}$ of both the multimodal and image-only models. As illustrated in the objective 2 (Obj$_2$) in Figure 2, for patch-based image inputs (or proposed regional features by object detectors), the entire patches of an image are swapped with another one within the sequence.

**Patch-Based.** We can perform the aforementioned swapping prediction in a finer granularity, directly on the image patches. Assuming each image $I_i$ is cropped into $w$ patches (or $w$ proposed regions for object detector’s case), i.e. $\{i_{1,i}, \ldots, i_{w,i}\}$, we randomly select $M$ (ranging from 1 to $w$) number of patches each from the two images $I_i, I_j$ (i.e. $\{i_{p,q}\}$, $p,q \in M$-sized sampled indices) to be swapped with probability $\delta$. Specifically, for each image patch $i_{w,m} \in I_i$, a randomly selected image patch $i_{w,n} \in I_j$ is sampled to be swapped with. The sampled $M$-sized indices do not need to be the same set of integers for each image. The objective 3 (Obj$_3$) in Figure 2 illustrates the patch-based swapping prediction when $w = 4$ and $M = 2$.

4.2.3 Masked Region Modeling (MRM)

Several V&L works propose to perform the masked learning objective on the visual modality, where a few image regions are masked out and the model is required to reconstruct those masked regions. The reconstruction target of MRM can be a pre-defined discrete visual token vocabulary (Sun et al., 2019; Bao et al., 2021), or (soft) object class la-

Figure 2: Sequentiality-aware pretraining includes: (1) the standard masked language modeling (MLM), (2) image-swapping prediction (IS), (3) patch-based image-swapping prediction (P-IS), and (4) sequence-based masked region modeling (MRM).
bel (Lu et al., 2019; Su et al., 2020; Chen et al., 2020a). In this work, we construct a feature-based target vocabulary dynamically at each mini-batch during training. Specifically, we first randomly select a same amount of $X\%$ ($X = 15$ in this work) patches for each image to be masked out, and then we construct a target vocabulary from the original output representations (before masking) of these patches. The selected patches are then replaced with 0-tensor as the special visual mask token.

Concretely, denote the output representation after feeding an input image-patch $i_{i,m}$ through the visual encoder (CLIP or ROI-Pooler) and the VisualBERT transformer as $h(i)_{i,m}$ and the masked positions of $I_i$ is $D_i$, we can construct a candidate list from all the output representations of the patches at the masked positions in each image, i.e. $C = \{h(i)_{i,m} \} \cup \{h(i)_{j,n}\}, m \in D_i, n \in D_j$. The image patches at the masked positions are replaced with a 0-tensor, denoted by $\text{mask}(i)_{i,m}$, and thus their output representations are $h(\text{mask}(i))_{i,m}$. For each output masked representation, we concatenate it with each of the candidate in $C$, i.e. $h(\text{mask}(i))_{i,m} || h(i')$, $\forall i' \in C$, which results in $|C|$ concatenated representations for each masked position. And hence a $|C|$-way multi-class classification can be performed (with a projection MLP added) by maximizing the probability of $p(i_{i,m}|h(\text{mask}(i))_{i,m}; C)$. Additionally, we perform the followings: (1) we randomly shuffle the candidate set $C$ for each masked position to prevent overfitting, and (2) we ensure the overlapping of masked positions in each pair of images, $D_i \cap D_j$, is $< 50\%$, which allows the models to utilize information of similar regions from other images in the sequence to enhance the sequential awareness.

### 4.3 Order Decoder – BERSON

BERSON is a recently proposed state-of-the-art neural sentence ordering framework (Cui et al., 2020), where a pointer network (Vinyals et al., 2016) exploits both the local (relative pairwise order) and global (self-attentions on top of the entire input sequence) information of the inputs to decode the predicted order. BERSON mainly exploits the [CLS] output representations for relational understanding (Figure 2). We replace the BERT model, which is the original input encoder module of BERSON, with our sequentiability-aware pretrained encoders across the three input modalities, and hence the output order can be decoded by BERSON’s pointer network module.

5 Experiments and Analysis

Our experiments seek to answer the following research questions: (1) How valid is the proposed task for humans to complete? (2) Is multimodality helpful? (3) How beneficial is the sequentiability-aware pretraining? (4) How would results differ when evaluating with alternative orders?

5.1 Evaluation Metrics

We adopt metrics below following existing works:

- **Position-Based** metrics concern the correctness of the absolute position of each item in a sequence. We consider: (1) **Accuracy (Acc)** which computes the ratio of absolute positions in the ground truth order that are correctly predicted; (2) **Perfect Match Ratio (PMR)** which measures the percentage of predicted orders exactly matching the ground truth orders; and (3) **Distance (Dist.)** which measures the average distance\(^8\) between the predicted positions of each item to its ground truth position.

- **Longest Common Subsequence** computes the average longest subsequences in common (Gong et al., 2016) between the predicted and ground truth orders ($L_q$). We also consider a stricter version, longest common substring, which requires the consecutiveness for the comparisons ($L_r$).

- **Kendall’s Tau ($\tau$) (Lapata, 2003)** is defined as $1 - 2 \times (#\text{ inversions})/(#\text{ pairs})$, where the inversion denotes that the predicted relative order of a pair of sequence items is inverted compared to the corresponding ground truth relative order, and $#\text{ pairs} = \binom{N}{2}$ for $N$-length sequence.

\[^8\]Except for distance metric, higher scores are better.
Each metric attempts to evaluate how good a predicted order is from different perspectives, i.e., position metrics concern the absolute correctness of the predictions, while common subsequence and $\tau$ metrics measure if the general sequential tendency is preserved despite incorrect absolute positions.

### 5.2 Experimental Setups

The description in each step is capped to have maximally 5 sentences for both the model inputs and the human annotations; and for the models the maximum input length per step is 60 tokens for training efficiency and GPU memory concerns, and hence the overall maximum input token length is 300. For the patch-based visual encoder, we adopt $32 \times 32$ patch for an input image reshaped to size $224 \times 224$, which results in $7 \times 7 = 49$ patches per image.

**Data Splits.** The original data splits are used in RecipeQA. For WikiHow, to prevent models’ exploiting knowledge from too similar articles, we split the data so that certain categories do not overlap in each split. Details are in Appendix Sec. A.1.

**Training Details.** Pretrained weights for each input encoder is obtained either directly from their corresponding code repositories or by running their codes on our setup. We select the model checkpoints to be evaluated using a held-out development split, specifically for WikiHow it is constructed from the same category distribution to the golden-test-set. Preliminary studies show that joint training with both RecipeQA and WikiHow data does not necessarily improve the downstream performance, thus the models evaluated in the two datasets are trained simply using their respective training sets.

### 5.3 Standard Benchmark Results

The results in this section are evaluated using the original ground truth orders obtained from the instruction manuals, where Section 5.4 discusses the results when alternative orders are considered. All the results are evaluated on the golden-test-set.

**Human Performance.** The IAAs of the human annotated orders in the WikiHow dataset, computed using the method described in Section 3.4, are 0.84, 0.82, and 0.69 for multimodal, text-only, and image-only variants of the task, respectively. They are 0.92, 0.87, and 0.81 for the RecipeQA dataset. The human performance for each input modality of the two datasets are as shown in Table 1. Consistently across the two datasets, multimodal version show significant improvements over the two unimodal counterparts.

Table 1 also summarizes the model performance on the golden-test-set. As can be noticed, the main competitions are between the multimodal and text-only models, whereas image-only variant serves as a baseline to lower bound the performance. In both datasets, compared under the same scenario, i.e., incorporating the sequentiality-aware pretraining or not, the two multimodal models consistently outperform their text-only counterparts.

The proposed sequentiality-aware pretraining is proven effective, especially for the patch-based multimodal models (CLIP-ViL). Table 2 summarizes a more detailed breakdown of the performance when different combinations of pretraining objectives are applied. However, there are still significant gaps between our top-performing model and the human performance, especially in the PMR metric. Additionally, we observe a different trend

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**Table 1: Golden-test-set performance:** Models which take multimodal inputs (for both VisualBERT and VisualBERT-CLIP encoders) consistently outperform the ones that only take unimodal inputs. Our proposed sequentiality-aware pretraining is shown consistently helpful throughout the three modality variants. Humans show larger performance gain when both modalities of inputs are provided, and are more robust to the local ordering as implied by the smaller gaps between $L_q$ and $L_r$.

| Modality        | Encoders | Pretrain | WikiHow Golden Test Set | RecipeQA Golden Test Set |
|-----------------|----------|----------|--------------------------|--------------------------|
|                 |          |          | | | | |
| Image-Only      | ResNet   | N        | 21.73 1.99 2.81 1.73 0.01 7.87 | 31.20 5.00 3.27 2.07 0.27 6.10 |
|                 | CLIP     | N        | 24.92 3.32 2.95 1.84 0.08 7.32 | 38.40 8.00 3.39 2.02 0.35 5.44 |
|                 | CLIP     | Y        | 28.24 4.98 3.09 1.96 0.16 6.80 | 47.20 16.00 3.68 2.40 0.52 4.12 |
| Text-Only       | RoBERTa  | N        | 74.75 56.81 4.47 3.78 0.82 1.71 | 74.00 52.00 4.45 3.68 0.83 1.64 |
|                 | RoBERTa  | Y        | 75.68 58.80 4.50 3.87 0.82 1.67 | 77.00 57.00 4.49 3.81 0.84 1.48 |
| Multimodal      | VisualBERT | N       | 75.30 57.10 4.45 3.83 0.81 1.65 | 76.20 58.00 4.49 3.85 0.83 1.58 |
|                 | VisualBERT | Y       | 77.30 59.40 4.50 3.86 0.83 1.58 | 78.20 60.00 4.56 3.91 0.85 1.44 |
|                 | CLIP-ViL | N        | 76.15 58.80 4.49 3.87 0.82 1.68 | 79.20 60.00 4.57 3.93 0.88 1.24 |
|                 | CLIP-ViL | Y        | 79.87 65.78 4.57 4.05 0.85 1.44 | 82.60 68.00 4.61 4.10 0.88 1.10 |
| Image-Only      | Human Performance | —       | 68.16 47.49 4.27 3.51 0.72 2.43 | 80.40 64.50 4.54 4.02 0.86 1.29 |
| Text-Only       | Human Performance | —       | 83.35 66.91 4.63 4.11 0.89 1.06 | 88.92 78.56 4.76 4.41 0.93 0.70 |
| Multimodal      | Human Performance | —       | 91.03 79.61 4.78 4.46 0.94 0.52 | 92.12 83.13 4.82 4.53 0.95 0.45 |
### Table 2: Model ablation studies
We detail the performance breakdown of different combinations of the pretraining objectives, on the best performing models from Table 1 for each dataset and modality.

| Modality          | Pretrain                  | WikiHow Golden Test Set | RecipeQA Golden Test Set |
|-------------------|---------------------------|-------------------------|--------------------------|
|                   | Acc↑ | PMR↑ | Lq ↑ | Lr ↑ | τ ↑ | Dist↓ | Acc↑ | PMR↑ | Lq ↑ | Lr ↑ | τ ↑ | Dist↓ |
| Image-Only        |      |      |      |      |     |       |      |      |      |      |     |       |
| IS                | 27.31 | 3.99 | 3.02 | 1.82 | 0.12 | 7.00 | 43.20 | 9.00 | 3.49 | 2.05 | 0.47 | 4.46 |
| IS + P-IS         | 27.57 | 4.65 | 3.07 | 1.93 | 0.16 | 6.85 | 43.40 | 12.00 | 3.57 | 2.24 | 0.48 | 4.46 |
| MLM               | 77.87 | 60.47 | 4.54 | 3.94 | 0.85 | 1.48 | 80.00 | 61.00 | 4.56 | 3.93 | 0.87 | 1.24 |
| Multimodal        | MLM + IS      | 78.21 | 63.00 | 4.57 | 3.99 | 0.87 | 1.24 | 78.21 | 62.13 | 4.55 | 3.97 | 0.84 | 1.50 |
| MLM + IS + P-IS   | 80.00 | 61.00 | 4.56 | 3.93 | 0.87 | 1.24 | 80.80 | 63.00 | 4.57 | 3.99 | 0.87 | 1.24 |

Figure 3: Top and least-5 categories of human-model performance difference (measured by PMR): The selected categories have >10 samples in the golden-test-set. The difference bars on the multimodal model series are compared against the text-only model series.

The selected categories have >10 samples in the golden-test-set. The difference bars on the multimodal model series are compared against the text-only model series.

In the two datasets where the multimodality benefit more in the RecipeQA dataset than WikiHow. The gap between the multimodal human and model performance is larger than the text-only counterpart in WikiHow, and exhibits a reversed trend in RecipeQA. We hypothesize that recipes may contain less common language usages and/or words for the pretrained language models and hence the multimodal pretraining can benefit more. Humans, on the other hand, benefit more from the images in WikiHow as the texts in WikiHow is hypothesized to contain more ambiguity.

#### 5.3.1 WikiHow Category Analysis

For WikiHow, we are particularly interested in which categories our models perform closer to human performance, as well as in which categories the multimodality is most helpful. In Figure 3 we select WikiHow categories with the top and least-5 (with PMR metric, top=3, least=2) performance gaps between the human and our best performing models in each modality. We observe that generally the categories of which multimodal model outperform text-only one the most are also the categories the models perform closest to human performance, such as Home and Garden. We hypothesize that the images in these categories are well complementary to the texts and that our sequentiality-aware grounding performs effectively, while for categories such as Arts and Entertainment and Hobbies and Crafts where humans still enjoy benefits from multimodality, our models have difficulty utilizing the multimodal information. We hypothesize that better visual understanding may alleviate the potentially suboptimal grounding as images of these categories can contain many non-common objects.

#### 5.4 Evaluating with Alternative Orders

For the each instance where alternative order(s) exist, we compute the best possible performance each predicted order can obtain across all the ground truth order(s), and denote it as the multi-reference performance. The subset of the golden-test-set where the instances are annotated with >1 ground truths are denoted as the multi-reference subset.

**Human Annotations.** The IAAs of the alternative order annotations in the WikiHow dataset, computed using the method described in Section 3.4, are 0.73, 0.71, and 0.78 for multimodal, text-only, and image-only variants, respectively. For RecipeQA, the IAAs are: 0.79, 0.76, and 0.79, respectively. The overall average number of ground truth references across the whole golden-test set becomes 1.19, 1.23, 1.09 for multimodal, text-only, and image-only variants of WikiHow; and 1.10, 1.17, 1.14 for RecipeQA. Table 3 lists the essential statistics of the multi-reference subsets.

**Performance Gains.** Table 4 summarizes the multi-reference performance of humans and the best performing models in each modality from Table 1. Several trends still hold: (1) Multimodality is helpful as multimodal performance is still significantly better than other modality counterparts, for both humans and models. (2) Human performance are still well above model performance even when multi-reference ground truths are considered. We question whether enforcing the original author-intended order to be the ground truth can cause unfairness to text-only models, as images can often better represent the details of the scene changes omitted by the texts, while in reality certain steps may not need to be performed strictly following
the author-written order. One can observe that the text-only modality indeed enjoys more benefits (Table 5 detail the percentage of the benefits in the multi-reference subset) when the ground truths are relaxed to have alternatives. However, combining with the aforementioned observation (1), it can be concluded that the textual contents indeed posses certain levels of ambiguities where images can help to disambiguate, but only a small proportion may be due to enforcing the original written order.

Qualitative Inspections. Figure 4 shows a few qualitative examples in different categories. Figure 4a shows that while step 1 and 3 may seem confusing with only looking at the texts, the images can help deciding the proper order, whereas models may fail to grasp such multimodal information in Figure 4b. In Figure 4c we show an example where multi-reference benefits both humans and the models, although in reality it should be more commonsensical to stir before refrigerating the mixtures. Table 6 lists the WikiHow categories with the most (top-5) agreed multi-reference ground truths. It is worth noting that the category with the most ground truths, Personal Care and Style, is also among the worst performance from both humans and models (Figure 3).

6 Related Works

Sequence Ordering. Story sequencing test is a popular way of examining children’s abilities on sequential reasoning of events and comprehending procedures. Many psychologists have studied this task and show it as evidence of procedural understanding (Tomkins, 1952; Baron-Cohen et al., 1986; Loucks et al., 2017). In NLP, existing works attempt the sequencing task as sorting a series of unordered sentences (Chen et al., 2016; Cui et al., 2018; Logeswaran et al., 2018; Oh et al., 2019; Lee et al., 2020). These existing works often attempt the sequencing task with sorting paper abstracts or short stories and article paragraphs (Calizzano et al., 2021). While certain prior work also attempts to extend the sequencing task to incorporate multimodality (Agrawal et al., 2016), the dataset used, Visual StoryTelling (Huang et al., 2016), the featured images were not intended to be procedural (or temporally coherent) nor supply unstates details to complement the texts. In computer vision, prior works leverage shuffle video frame prediction for learning video representations (Lee et al., 2017; Xu et al., 2019; Wang et al., 2020) and multimodal video understanding (Li et al., 2020). We take one step further than the existing works to tackle the multimodal sequencing task using complex task descriptions in instructional manuals, associated with images intended to complement the texts.

Task/Procedure Understanding. Several existing works have also utilized WikiHow for learning to understand task knowledge, specifically in NLP, textual descriptions of WikiHow have been used for abstractive summarization (Koupaee and Wang, 2018), procedural understanding (Zhou et al., 2019; Tandon et al., 2020), and intent estimation (Zhang et al., 2020a). As WikiHow includes multimodal information for task knowledge, concurrent work also uses it as a resource for understanding visual goals (Yang et al., 2021). We believe our work on utilizing WikiHow as a resource for the sequencing task can help advancing towards the goal of comprehensive multimodal procedural understanding.

Multimodality. Beside VisualBERT and CLIP-ViL used in this work, there are several recent works on advanced multimodal grounding techniques (Tan and Bansal, 2019; Li et al., 2019; Lu et al., 2019; Lu et al., 2019; Su et al., 2020; Chen et al., 2020b; Huang et al., 2020; Wen et al., 2021). We utilize VisualBERT and CLIP-ViL for their simplicity to be adapted the to our task and easier integration to our sequentiality-aware pretraining objectives as well as the BERSON decoder module, however, our framework is able to incorporate any of the aforementioned multimodal models.

7 Conclusions

In this work we present studies of language and multimodal models on the procedure sequencing task, leveraging popular online instructional manuals. Our experiments show that both multimodality and our proposed sequentiality-aware pretraining are helpful for the multimodal sequencing task, however, the results also highlight significant gaps.

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The images come from photo albums and the annotators create stories based on their freely arranged image sequences.
We again only list the categories with total instance count >10.

Table 6: Top-5 mean alternative orders by categories: We list top-5 categories in WikiHow according to the number of average ground truth references in their multi-reference subset. We again only list the categories with total instance count >10.

below human performance (~15% on PMR).

We provide insights as well as resources, such as the multi-reference annotation of the sequenc-ing task, to spur future relevant research. We also anticipate that the alternative orders defined and annotated in our work can benefit more comprehensive task procedure understanding, future works such as predicting task steps which can be parallel and/or interchangeable, and understanding instruction step dependencies are interesting extensions of this work.

Table 4: Multi-reference performance with alternative orders: † denotes results from human performance. We include performance of each subset categorized by whether the instance have more than one ground truth orders (denoted as Multi.) or just the original ground truth order (denoted as Single). For the multi-reference subset, we show the performance evaluated (Eval) using either single or multiple reference. Performance are denoted as Perf. type where as Gain denotes the performance gain (in percentage) of the overall multi-reference performance compared to the performance in Table 1.

Table 5: Multi-reference benefits: We report the actual percentage of multi-reference subset which benefits from the multi-reference ground truths. The benefits are defined as if the performance of an instance increase after evaluating with multi-reference ground truths.

Table 6: Top-5 mean alternative orders by categories: We list top-5 categories in WikiHow according to the number of average ground truth references in their multi-reference subset. We again only list the categories with total instance count >10.

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How To Clean Platinum

1. Line a pan with tin foil. A cookie sheet should work as long as it is deep enough to fit your platinum.
2. Mix your base solution. Combine one cup of boiling water with one tablespoon of salt and one drop of hot glue.
3. Pour the solution over your platinum. Gently pour the boiling water into the pan.
4. Roll a single of white sugar into a ball. The sugar will solidify the base solution.
5. Rinse and dry your platinum. Remove your jewelry from the pan. Rinse under running water and rinse.

Best Model Predictions

- Multimodal Alt. GTs: [N/A]
- Multimodal Model: 1-2-3-4-5 (0.6/1.0)
- Text-Only Alt. GTs: [32145]
- Text-Only Model: 3-2-4-5 (0.6/1.0)
- Image-Only Alt. GTs: [N/A]
- Image-Only Model: 5-2-4-1-3 (0.2/0.2)

How To Make a Candy Cake

1. In a saucepan, melt one package of miniature marshmallows, ¾ cup of boiling water with one tablespoon of salt and one drop of hot glue.
2. Mix your base solution.
3. Pour the mixture over your platinum. Gently pour the boiling water into the pan.
4. Roll sugar into a ball. The sugar will solidify the base solution.
5. Rinse and dry your platinum. Remove your jewelry from the pan. Rinse under running water and rinse.

Best Model Predictions

- Multimodal Alt. GTs: [N/A]
- Multimodal Model: 1-2-3-4-5 (0.6/1.0)
- Text-Only Alt. GTs: [32145]
- Text-Only Model: 3-2-4-5 (0.6/1.0)
- Image-Only Alt. GTs: [N/A]
- Image-Only Model: 5-2-4-1-3 (0.2/0.2)

How To Make a Yarn Pumpkin

1. Find a small, plastic pumpkin to use as your base. If you can’t find one, you can use a Styrofoam ball instead.
2. Secure the end of your yarn to the base of your pumpkin with a drop of hot glue.
3. Start wrapping the yarn around your pumpkin, gluing at each wrap.
4. Consider wrapping a piece of green paper around the stem.
5. Secure your pumpkin up. Trim off any loose bits of yarn, and glue down any bits that stick.

Best Model Predictions

- Multimodal Alt. GTs: [15342]
- Multimodal Model: 3-2-4-5 (0.6/1.0)
- Text-Only Alt. GTs: [12435]
- Text-Only Model: 2-3-5-1-4 (0.0/0.0)
- Image-Only Alt. GTs: [N/A]
- Image-Only Model: 5-2-4-1-3 (0.2/0.2)

How To Clean Platinum

1. Line a pan with tin foil. A cookie sheet should work as long as it is deep enough to fit your platinum.
2. Mix your base solution. Combine one cup of boiling water with one tablespoon of salt and one drop of hot glue.
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- Text-Only Alt. GTs: [32145]
- Text-Only Model: 3-2-4-5 (0.6/1.0)
- Image-Only Alt. GTs: [N/A]
- Image-Only Model: 5-2-4-1-3 (0.2/0.2)

Making a Magic Candy Cake

1. In a saucepan, melt one package of miniature marshmallows, ¾ cup of boiling water with one tablespoon of salt and one drop of hot glue.
2. Mix your base solution.
3. Pour the mixture over your platinum. Gently pour the boiling water into the pan.
4. Roll sugar into a ball. The sugar will solidify the base solution.
5. Rinse and dry your platinum. Remove your jewelry from the pan. Rinse under running water and rinse.

Best Model Predictions

- Multimodal Alt. GTs: [N/A]
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Recipe Sample

1. Melt the marshmallows. In a saucepan, melt one package of miniature marshmallows, in cup of candy oil.
2. Consider wrapping a piece of green paper around the stem.
3. Secure the end of your yarn to the base of your pumpkin with a drop of hot glue.
4. Start wrapping the yarn around your pumpkin, gluing at each wrap.
5. Take the cake out of the pan. Dip the pan in hot water for 5 10 seconds.

Best Model Predictions

- Multimodal Alt. GTs: [N/A]
- Multimodal Model: 1-2-3-4-5 (0.6/1.0)
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- Image-Only Alt. GTs: [N/A]
- Image-Only Model: 5-2-4-1-3 (0.2/0.2)
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A Details of Datasets

A.1 Detailed Statistics

WikiHow Categories: The category in WikiHow generally forms a hierarchical directed acyclic graph. Each category can have its relevant subcategory, which usually spans finer granularity of category types. For example, a possible category traversal path is: Cars and Vehicles → Public Transport → Air Travel, which can lead to the article How to Overcome the Fear of Flying\(^\text{10}\). We attach these full category traversal paths as an additional feature to each of the article in our dataset, and we also will provide a complete list of the taxonomy composed by all the categories and subcategories in WikiHow. We include the category-data counts in Table 8 for a reference, where we only show the top-level category here. The more in-depth categories can be referred to in the full released version of the dataset.

Train-Test Splits: For RecipeQA we use the original data splits which ensure no identical recipe appears in more than one set (each recipe has its unique recipe-id). For WikiHow, we split the data according to the third level category to prevent models from exploiting too similar task knowledge in the same category, where the level (three) is empirically decided. This will ensure that no articles belonging to the same third-level category should appear in more than one set. We also prioritize categories that are more likely to be procedural (concerning more physical knowledge) for the test sets, such as Cars and Vehicles, Hobbies and Crafts, and Home and Garden. We split the WikiHow dataset into train, development, and test set, where our human-annotated golden-test-set is a subset of this (larger) test set, which is sampled and manually inspected by internal members to ensure high quality. Table 7 presents the more detailed essential statistics of the two datasets, WikiHow in Table 7a, and RecipeQA in Table 7b.

B Models

B.1 WikiHow Images

Although the images in WikiHow can often be synthetic or "cartoon-ish", we observe that modern strong object detectors can still propose meaningful regions, regardless of whether the object class prediction is sensible or not. We include some predicted bounding boxes in Figure 6 for references. And hence, although there may be concerns on sub-optimal visual understanding from these images, we do believe both of our ResNet and CLIP visual

\(^{10}\)https://www.wikihow.com/Overcome-the-Fear-of-Flying

| Type Counts |
|-------------|
| Total Unique Articles | 109486 |
| Total Unique Images | 1521909 |
| Train / Dev / Test / Human | 98268 / 5459 / 5759 / 300 |
| Type-Token Ratio | 216434 / 82396591 = 0.0026 |

| Type Counts |
|-------------|
| Total Unique Articles | 10063 |
| Total Unique Images | 87840 |
| Train / Dev / Test / Human | 8032 / 973 / 1058 / 100 |
| Type-Token Ratio | 91443 / 5324859 = 0.017 |

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Table 7: General statistics of the two datasets: We provide the detailed component counts of the datasets used in this work, including the statistics of tokens and sentences from the step instructions (lower half of the two tables).

| Categories | Counts |
|------------|--------|
| Arts and Entertainment | 4675 |
| Cars and Other Vehicles | 2044 |
| Computers and Electronics | 15023 |
| Education and Communications | 7406 |
| Family Life | 1747 |
| Finance and Business | 6228 |
| Food and Entertaining | 7670 |
| Health | 8800 |
| Hobbies and Crafts | 9217 |
| Holidays and Traditions | 736 |
| Home and Garden | 9460 |
| Personal Care and Style | 6523 |
| Pets and Animals | 5281 |
| Philosophy and Religion | 828 |
| Relationships | 2877 |
| Sports and Fitness | 3271 |
| Travel | 746 |
| Work World | 1579 |
| Youth | 2389 |
| Others | 21 |

Table 8: Top-Level Categories of WikiHow: Number of unique manuals in each top-level category of the WikiHow dataset. The categories are sorted by alphabetical order. In total there are 19 these top-level categories (same as what this page indicates: https://www.wikihow.com/Special:CategoryListing), and one "others" category for standalone leaf node categories without real linkages to these top-level categories.
encoders can extract reasonably useful features.

B.2 Training & Implementation Details

Pretrained Weights. All the input encoders are initialized with their respective large-scale pre-trained weights, and we use Faster-RCNN with feature pyramid networks (Lin et al., 2017) for encoding the images.

All the benchmarked models are trained on a single Nvidia A100 GPU on a Ubuntu 20.04.2 operating system. The hyperparameters for each model are manually tuned against different datasets, and the checkpoints used for testing are selected by the best performing ones on the development set.

The implementations of the transformer-based models are extended from the huggingface code base (Wolf et al., 2020), and our code-base is implemented in PyTorch. The computer vision detector model used in one of our image-only encoders, ResNet-based Faster-RCNN (Ren et al., 2016), adopts the detectron2 open sourced module, and their pretrained weights are obtained from the official implementations from Facebook AI Research. Implementations of BERSION-based models are adapted from the original author’s implementation, where more details can be found in their paper. Implementation of the VisualBERT is obtained from the MMF framework from Facebook AI Research, and CLIP-ViL model is obtained and adapted from the original author’s released code repository. We use the same repository for the image-only encoder CLIP.

B.3 Hyperparameters

For the sequencing task, we train all the models for 5 or 10 (multimodal models) epochs for all the model variants, where the training time varies from 2-4 hours for the text-only models and 6-8 hours for the multimodal models. We list all the hyperparameters used in Table 9. We also include the search bounds and number of trials in Table 10, all of our models adopt the same search bounds and the same ranges of trials.

C Details of Human Annotations

C.1 Golden-Test-Set Selections

In order to curate a high-quality test set for humans to evaluate, we manually select the samples which meet our general criteria: (1) the tasks are procedural in both texts and images (2) the task’s images are designed to complement the text descriptions or provide a more illustrative information for some unstated implicit knowledge. We ask three of our internal members (co-authors) to perform such manual selections, and preserve ones that have majority votes. In total, we select 300 samples for WikiHow and 100 samples for RecipeQA.

C.2 General Annotation Procedure

We collect the human performance via Amazon Mechanical Turk (MTurk). Each MTurk worker in our human study is required to read the provided instruction carefully, which is shown in Figure 5a, and then perform the task, which consists of an intuitive drag-n-drop task (illustrated in Figure 5b.). Each MTurk HIT is designed to have five sets of sequencing tasks, where each set has the aforementioned sequencing task followed by a few additional questions such as confidence level of the worker when inferring the order, and whether different modalities are helpful in a particular task. For each unique sample in the selected golden-test-set, we construct two annotation sets. In one, there is only the textual description, and in the other one, there is multimodal information. We launch the HITs containing the same sample but with different modalities with a week gap to prevent potential memorization if the same worker happens to annotate the exactly identical data sample. We estimate the time required to complete each of our HITs to be 10-15 minutes. We adjust our pay rate accordingly to $2 or $3 USD depending on the length of the task. This roughly equates to a $12 to $15 USD per hour wage, which is above the local minimum wage for the workers.

In total we receive annotated HITs from around 80 workers for WikiHow, and 14 workers for RecipeQA. The Pearson correlation between the performance of the qualification samples and the overall HIT performance is 0.6 with p-value < 0.05. Since it is of positive correlation and significant, we censor assignments with substantially low overall performance (<20% on accuracy metric), and relaunch the HITs containing those samples for a few more rounds for higher quality annotations.

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11https://www.nvidia.com/en-us/data-center/a100/
12https://github.com/huggingface/transformers
13https://pytorch.org/
14https://github.com/facebookresearch/detectron2
15https://github.com/facebookresearch/mmf
16https://github.com/clip-vil/CLIP-ViL
Table 9: Hyperparameters used in this work: Initial LR denotes the initial learning rate. All the models are trained with Adam optimizers (Kingma and Ba, 2015). We include number of learnable parameters of each model in the last column, denoted as #.params.

| Modality          | Models               | Batch Size | Initial LR | # Training Epochs | Gradient Accumulation Steps | # Params     |
|-------------------|----------------------|------------|------------|-------------------|----------------------------|--------------|
| Image-Only        | ResNet               | 4          | $5 \times 10^{-6}$ | 5                 | 1                          | 112.98M      |
|                   | CLIP                 | 4          | $5 \times 10^{-6}$ | 5                 | 1                          | 88.08M       |
| Text-Only         | RoBERTa              | 4          | $5 \times 10^{-6}$ | 5                 | 1                          | 393.16M      |
| Multimodal        | VisualBERT           | 4          | $5 \times 10^{-6}$ | 10                | 1                          | 421.32M      |
|                   | VisualBERT-CLIP      | 4          | $5 \times 10^{-6}$ | 10                | 1                          | 497.40M      |
| Image-Only Pretrain | CLIP               | 4          | $1 \times 10^{-5}$ | 5                 | 1                          | 68.09M       |
| Text-Only Pretrain | RoBERTa             | 4          | $1 \times 10^{-5}$ | 5                 | 1                          | 355.36M      |
| Multimodal Pretrain | VisualBERT       | 4          | $1 \times 10^{-5}$ | 5                 | 1                          | 383.52M      |
|                   | VisualBERT-CLIP      | 4          | $1 \times 10^{-5}$ | 5                 | 1                          | 465.50M      |

Table 10: Search bounds: for the hyperparameters of all the models.

| Type                  | Batch Size | Initial LR | # Training Epochs | Gradient Accumulation Steps |
|-----------------------|------------|------------|-------------------|----------------------------|
| Bound (lower–upper)   | 2–8        | $1 \times 10^{-5}$–$1 \times 10^{-6}$ | 3–10 | 1–2 |
| Number of Trials      | 2–4        | 2–3        | 2–4              | 1–2                         |

C.3 Statistics

In addition to the human performance provided in Table 1 in the main paper, we provide two more statistics obtained from the workers: the percentages of confidence levels and which modality (modalities) help for deciding the order.

**Confidence Levels.** As shown in Table 12, majority of workers feel at least fairly confident (score of 4) about their predictions, which can justify the validity of our selection of golden-test-set.

**Modality Helps.** As which modality is potentially more helpful, we include the percentages of each answer category in Table 11. It can be noticed that majority of workers (> 60%) think that multimodal (both modalities) is helpful, and especially in the recipe data, there are > 90% of workers indicating the effectiveness of utilizing multimodal inputs.

For annotating the alternative orders, in total we receive HITs from around 70 workers for WikiHow, and 40 workers for RecipeQA, and note that we deliberately exclude the workers who have participated in the standard ordering task. The monetary rewards and other general settings follow the same procedure as in the standard performance collection. We compute pairwise IAAAs for each worker against every other workers, using the method described in Section 3.4, and then we place a threshold to filter out workers that tend to have too low IAAAs (which is a likely indicator that a worker is either a spammer or not understanding our task well).

Table 11: Which modality helps? We compute the percentage of each answer category. In both datasets, majority of the annotations indicate that both modality are helpful for deciding the orders.

| Confidence Level | WikiHow | RecipeQA |
|------------------|---------|-----------|
| 5 (Very)         | 54.61   | 64.75     |
| 4 (Fairly)       | 27.38   | 23.00     |
| 3 (Moderately)   | 12.24   | 7.00      |
| 2 (Somewhat)     | 5.21    | 4.75      |
| 1 (Not-At-All)   | 0.56    | 0.50      |

Table 12: Confidence Level Statistics (%): In both datasets, majority (> 80%) of the annotators indicate at least > 4 (fairly) confidence level, which can help justifying the validity of the human performance.

Dataset | Both | Text-Only | Image-Only | Neither |
---------|------|-----------|------------|---------|
RecipeQA | 90.4 | 1.0       | 8.6        | 0.0     |
WikiHow  | 62.9 | 33.7      | 2.4        | 1.0     |
**Sequence the Events:**

**[Please Read]** The goal of this MTurk task is to sort 5 sets of initially randomly ordered events, sampled from several steps of our collected visual instructional manuals, with (a) [image](image1.png) specified. We request that you put them into the proper order that you think they should occur (or need to be performed in). We ask you to do the following two things:

1. **Guide the blocks:** Drag each block in the first row into its appropriate slot in the second row. As long as the color of the block changes in the bin you choose, it is a proper action. No need to perfectly fill the blocks into some bins. (But of course it is more desired.)
2. **Answer the questions:** For each set, there are some follow-up questions to be answered, make sure to put your choices for each of them.

Some set may not come with images and is intended to be used as a control.

**NOTES:**

- **If you happen to find some glitches, e.g., clickable questions overlapping, please try to refresh your browser to find the most suitable resolution.**
- **One of the (b) is intended to be relatively simple and used as a qualification sample to filter spamming inputs.**

Please try your best for each set as the rewards may be affected upon detecting spamming inputs.

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**(a) Instructions**

**Set 3: Caprese Salad With Cilantro**

(a) [Image](image2.png)

(b) [Image](image3.png)

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**(b) Proposed Annotation Interface**

**Figure 5: MTurk Annotation User Interface:** (a) We ask the annotator to follow the indicated instructions, and perform the sequencing task. (b) The annotation task is designed for an intuitive drag-and-drop usage, followed by a few additional questions such as confidence level and whether each modality helps. (This example is obtained from RecipeQA dataset.)

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**(a) Detected Image Regions 1**

(b) Detected Image Regions 2

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**Figure 6: Proposed image regions by Detectron2:** We show some examples that even these synthetic and cartoon-ish images in the WikiHow dataset can provide meaningful representations which can be utilized by strong pretrained object detection modules. We show few top-detected objects with their bounding boxes and predicted classes. Note that the classes may be wrongly predicted, the proposed regions are all meaningful.