Unsupervised Script Generation from Narrations of Instructional Videos

Anonymous ACL submission

Abstract

This work explores the problem of generating *scripts* of real-world activities. Different from prior formulations, we consider a setting where text transcripts of instructional videos performing a real-world activity (e.g., making coffee) are provided and the goal is to identify the key steps relevant to the task as well as the dependency relationship between these key steps. We propose a novel script generation approach that combines the reasoning capabilities of instruction-tuned language models along with clustering and ranking components to generate accurate scripts in a completely unsupervised manner. We show that the proposed approach generates more accurate scripts compared to a supervised script learning approach on tasks from the Procel and Crosstask datasets.

1 Introduction

Humans have a remarkable ability to understand and reason about the intermediate steps to achieve a certain goal. Strong commonsense priors allow us to understand the complex relationships between these steps without being explicitly taught. Being able to reason about such *scripts* of real-world tasks is thus of central importance to artificial agents in order to efficiently learn and perform new tasks.

Script understanding has a long history in AI (Schank and Abelson, 2013). Early work studied scripts in the form of narrative chains (Chambers and Jurafsky, 2008; Pichotta and Mooney, 2016). Regneri et al. (2010) and Modi and Titov (2014) generate temporal script graphs using sequence alignment approaches. Recent work formulate the script generation problem as generating a sequence of key steps from a given scenario (e.g., bake a cake) (Sakaguchi et al., 2021; Sancheti and Rudinger, 2021). Pal et al. (2021); Wu et al. (2022) take an information extraction perspective and model relationships between entities and sentences extracted form procedural text to generate flow graphs. Multimodal script learning approaches have been proposed to identify key steps from videos and associated transcripts (Elhamifar and Naing, 2019; Zhukov et al., 2019; Zellers et al., 2021). Scripts have also been studied in the context of planning in AI agents for completing tasks (Logeswaran et al., 2022; Huang et al., 2022).

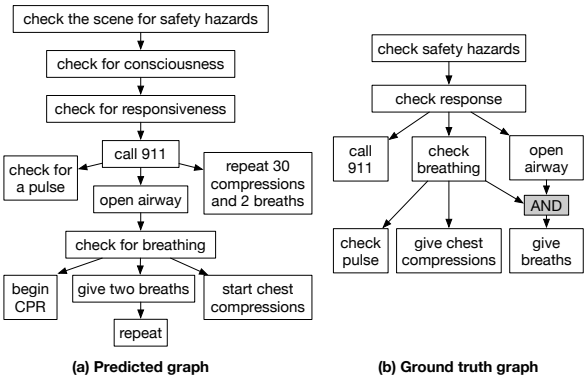

Figure 1: Predicted (a) and ground truth (b) graphs for the *perform cpr* task. Edges indicate precondition relationships. Steps with multiple preconditions are represented using an AND node.

Our focus in this work is to generate a directed graph that represents dependency relationships between the key steps relevant to a real-world task. Figure 1 (a) shows a graph predicted by our approach for *performing CPR*. An example dependency that can be read from the graph is that checking for safety hazards has to have happened before any other step (i.e., it is a *precondition* that needs to be satisfied). In this paper, we will use the term *script* to refer to such dependency graphs.

More formally, consider a real-world *task* τ. We assume that multiple text *transcripts* $t_1, \ldots, t_n$ describing how this task is performed are available.[1] We assume that having access to such multiple transcripts helps robustly identify the dependencies between key steps so that an accurate script can be

[1]Each transcript is a text document derived from instructional videos using Automatic Speech Recognition.

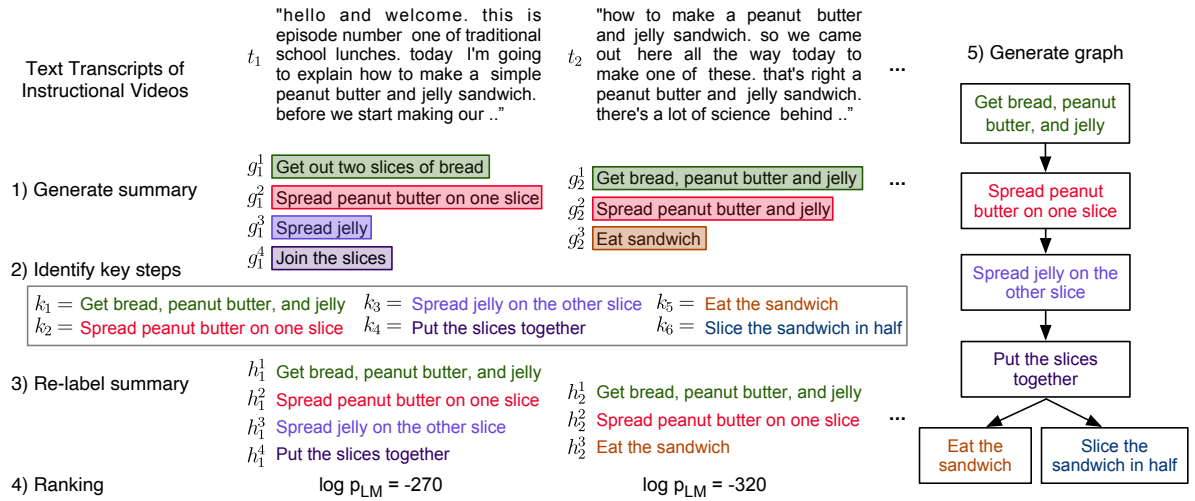

Figure 2: **Overview of our Script Generation Pipeline.** Given multiple text transcripts of a task, we 1) Summarize the steps described in the transcript, 2) Identify the key steps, 3) Re-label summary steps with key steps, 4) Rank sequences using a language model and 5) Consolidate top-k sequences to generate a script for the given task.

generated. For instance, if step y frequently follows step x, it is highly likely that step x needs to happen before step y (i.e., is a *precondition*). Our goal is to generate a *script* for the given task τ which models these dependencies. In particular, this involves (i) Identifying the *key steps* $K = \{k_1, \ldots, k_m\}$ relevant to performing the task and (ii) Generating a graph with nodes k_i and edges representing precondition relationships.

Our contributions in this work are as follows.

- We propose an unsupervised script generation pipeline that uses pretrained language models to infer key steps and their dependencies from multiple text descriptions of a real-world activity.
- We propose ranking and filtering mechanisms to improve the quality of generated scripts.
- We demonstrate the effectiveness of the proposed approach compared to strong supervised and unsupervised baselines on two datasets.

2 Approach

Our approach to script generation consists of multiple steps, illustrated in Figure 2. First, we use an instruction-tuned language model to generate a summary of steps (in free-form text) from a transcript (Section 2.1). Given these *summary step sequences* generated from multiple such transcripts for the task, we identify the key steps relevant to the task using a clustering approach (Section 2.2). We then re-label *summary step sequences* using the identified key steps to obtain *key step sequences* (Section 2.3) and rank them using a language model (Section 2.4). Finally, we generate a script for the task from the key step sequences (Section 2.5).

2.1 Generating Summary Steps

The first step of our pipeline extracts a summary of steps $g_i = (g_i^1, g_i^2, \ldots)$ of performing the task described in each transcript t_i. We use an instruction-tuned language model for this purpose. We prompt the model with a transcript, followed by a query such as *'Based on this description list down the key steps for making coffee using short phrases.'* and let the model generate a completion. We use the 'Davinci' version of the InstructGPT (Ouyang et al., 2022) model in our experiments. We observed that the model consistently generates the steps in the format '1. `<step 1>`\n 2. `<step 2>`\n ..', occasionally using bullet points instead of numbers. The sentences g_i^j on each line are extracted and treated as the summary steps identified from the transcript. Appendix B shows example summary step sequences generated by InstructGPT.

2.2 Identifying Key Steps Relevant to the Task

Given summary step sequences $g_1, \ldots, g_n$ generated in the previous step, we seek to identify correspondences between steps in different summaries and capture the salient steps that appear frequently. We use a clustering approach for this purpose. Sentences g_i^j are represented as embeddings using a sentence encoder (We use the MiniLMv2 encoder from the SentenceTransformers library (Reimers and Gurevych, 2019; Wolf et al., 2019), which was identified as the best sentence embedding method for semantic search/retrieval). We obtain high-confidence clusters by identifying *max cliques* – clusters of sentences that are similar (determined by a threshold - cosine similarity ≥ 0.9) to each

other, and retain cliques with more than 5 sentences. We noticed that this often yields multiple clusters that represent the same key step. For instance, the steps '*fill the moka pot with water*' and '*fill the bottom chamber with water*' represent the same key step of filling water, but are placed in different clusters. Identifying such redundant clusters based on sentence similarity alone is difficult. We define the notion of *sequence overlap* between two clusters – how often a sentence from one cluster and a sentence from the other cluster appear in the same summary step sequence. Intuitively, if two clusters have high inter-cluster similarity and low *sequence overlap*, it is likely that they represent the same key step, and we merge the clusters. The resulting clusters obtained are treated as the key steps $k_1, \ldots, k_m$.[2] Appendix C shows example clusters discovered for different tasks.

2.3 Re-labeling Summary Step Sequences

We re-label each summary step sequence g[3] with the identified key steps $k_1, \ldots, k_m$ to produce a *key step sequence* h using the greedy algorithm described in Algorithm 1. The algorithm sequentially picks the most similar[4] candidate summary step and cluster pair (g^a, k_b) at each step, assuming each key step only appears once in the sequence. The process terminates when the highest similarity drops below zero.

2.4 Ranking

One shortcoming of the labeling algorithm described in the previous section is that it does not take the sequential nature of steps into account. To alleviate this issue, we use a language model to identify and filter the most promising key step sequences. Specifically, we use $\log p_{\text{LM}}(h|\text{prompt})$ as a measure of the quality of the key step sequence h, where we compute the likelihood of h given a prompt similar to the prompt in Section 2.1 under a pre-trained language model. Multiple labelings are ranked based on this measure using a GPT2-XL model (Radford et al., 2019) and the top-k are chosen as confident predictions for graph generation ($k = 75\%$ in our experiments).[5]

[2]We use *cluster* and *key step* interchangeably. For visualization purposes we represent a cluster using a random sentence in the cluster.

[3]Subscript i dropped for brevity.

[4]defined as the maximum cosine similarity between g^a and any sentence in cluster k_b i.e., $\max_{s \in k_b} cos(g^a, s)$

[5]We use an open source language model considering API costs. Further, GPT2-XL led to decent ranking performance.

Algorithm 1: Key Step Sequence Inference

Input $g = (g^1, g^2, \ldots)$ ▷ Summary step sequence
Input $K = \{k_1, k_2, \ldots\}$ ▷ Key steps
For each summary step identify most similar sentence from each cluster:
$C_{ij} \leftarrow \max_{s \in k_j} cos(g^i, s)$
$H_{ij} \leftarrow \arg\max_{s \in k_j} cos(g^i, s)$
$S \leftarrow \{\}$ ▷ Predicted alignments
while $\max_{i,j} C_{ij} > 0$ **do**
  $a, b \leftarrow \arg\max_{i,j} C_{ij}$
  $S \leftarrow S \cup \{(a, b)\}$
  $C_{aj} \leftarrow 0, C_{ib} \leftarrow 0 \quad \forall i, j$
Sort $(a_i, b_i) \in S$ so that $a_1, a_2, \ldots$ are in increasing order
Output $h = (H_{a_1 b_1}, H_{a_2 b_2}, \ldots)$ ▷ Key step sequence

2.5 Script generation

We use an off-the-shelf algorithm (Sohn et al., 2020; Anonymous, 2022) which is based on Inductive Logic Programming (ILP) for constructing a graph from key step sequences $h_1, \ldots, h_n$. Inuitively, the algorithm identifies a set of preconditions (which key step must precede another key step due to a causal relationship) most consistent with the key step sequences. Details of the algorithm can be found in Appendix A.

3 Experiments

Data We use Procel (Elhamifar and Naing, 2019) and Crosstask (Zhukov et al., 2019) datasets in our experiments. We experiment with five tasks from each dataset (considering API costs). Task in these two datasets have respectively 13 and 7 key steps on average. We use 60 instances for each task, where each instance is an instructional video along with its text transcript. The transcripts have 565 tokens on average.

Setup The datasets come with key steps annotations (i.e., K) for each task and key step sequence annotations for each transcript. Our approach is unsupervised and does not make use of these annotations. However, for evaluation purposes, we consider two settings. The first setting assumes ground truth K and evaluates the performance of the full pipeline ignoring the clustering component (since key steps are known). In the second setting, we use K inferred from Section 2.2 and perform qualitative comparisons with ground truth graphs. Note that we did not use *key step sequence* annotations from the datasets in either setting.

3.1 Results

Known Key Steps Table 1 compares our approach with baselines on graph prediction accuracy. We use ground truth human annotated graphs

Model	Procel (Accuracy ↑)						Crosstask (Accuracy ↑)					
	(a)	(b)	(c)	(d)	(e)	Avg	(f)	(g)	(h)	(i)	(j)	Avg
① Proscript (Sakaguchi et al., 2021)	65.0	51.8	46.9	52.1	53.6	53.9	52.3	**89.6**	57.0	**62.5**	61.4	64.6
② ASR → Labels → Graph	52.5	57.1	78.1	**59.4**	53.6	60.1	54.5	72.9	**71.1**	56.2	54.5	61.8
③ ASR → VPs → Labels → Graph	52.5	53.6	56.2	**59.4**	53.6	55.1	54.5	72.9	**71.1**	56.2	59.1	62.8
④ ASR → GPT → Labels → Graph	68.8	69.6	87.5	53.1	55.4	66.9	**75.0**	72.9	61.7	**62.5**	65.9	67.6
⑤ ASR → GPT → Labels → Rank → Graph	**76.2**	**80.4**	**90.6**	51.0	**62.5**	**72.1**	72.7	77.1	61.7	**62.5**	**68.2**	**68.4**
⑥ Ground-truth labels → Graph	82.5	83.9	78.1	78.1	96.4	83.8	79.5	89.6	68.0	68.8	72.7	75.7

Table 1: Graph prediction accuracy on Procel and CrossTask datasets. The tasks are (a) make PBJ sandwich (b) change iphone battery (c) perform CPR (d) set up chromecast (e) tie tie (f) change tire (g) make latte (h) make pancakes (i) add oil to car (j) grill steak. Baselines ②, ③, ④ differ in the inputs used for key step labeling (i.e. Algorithm 1) – they respectively use the ASR sentences, verb phrases extracted from the ASR and summary steps generated by GPT (Section 2.1). ⑤ is our proposed approach which includes top-k filtering (Section 2.3). ⑥ shows graph generation performance with ground truth key step sequences.

from Anonymous (2022) for evaluation. Proscript (Sakaguchi et al., 2021) is a language model fine-tuned on manually curated script data. Given a task description and a set of key steps, Proscript generates a partial order of the key steps. In addition, we consider several variations of our approach as baselines in Table 1.

First, we observe that our unsupervised approach performs better than the proScript baseline which was explicitly trained on script data. Second, using GPT generated summaries for labeling (④) performs better than directly labeling the ASR sentences (②) or verb phrases (VPs) extracted from the ASR (③). This baseline is inspired by prior work (Alayrac et al., 2016; Shen et al., 2021) which extract verb phrases from transcripts and attempt to identify salient actions using filtering/alignment mechanisms. These approaches are susceptible to noise in the text data and are further limited by the assumption about each step being represented by a short verb phrase (extracted using syntax templates). In contrast, we exploit large language models in order to extract key phrases from the transcript. Third, we observe that ranking and filtering key step sequences using a language model (⑤) further improves performance, with a significant improvement for Procel. Finally, our approach comes closest to graphs generated from human annotated key step sequences in the datasets (⑥).[6] Appendices E and F further present ablations showing the impact of modeling choices in our pipeline.

Unknown Key Steps Next, we consider the full pipeline where key steps are identified automatically. Since ground truth reference scripts are unavailable in this case we perform a qualitative comparison of graphs generated using our approach and the ground truth, human annotated graph. Figures 1 and 2 show predicted graphs for the tasks *perform cpr* and *make pbj sandwich*, respectively.

We observe that the predicted graph for *perform cpr* is more detailed and fine-grained than the ground truth graph and captures many of the ground truth precondition relationships. On the other hand, the graph for *make pbj sandwich* is less fine-grained compared to the ground truth (Figure 9b of Appendix D). For instance, the ground truth annotations distinguish between *putting jelly on the bread* and *spreading jelly on the bread*, whereas our approach treats them as a single step. In addition, spreading peanut butter and spreading jelly are independent of each other and have no sequential dependency. However, the predicted graph fails to capture this and assumes that the former is a precondition for the latter. Appendix D shows more examples of predicted graphs.

4 Conclusion and Limitations

This work presented an unsupervised approach to generate scripts from text narrations of instructional videos. Our framework exploits multiple text transcripts which describe a task in order to robustly identify dependencies between key steps. We demonstrated the effectiveness of our approach compared to several baselines. A limitation of our work is the GPT API cost associated with scaling to a large number of tasks, which can be addressed by the use of large open-source language models. Our work can be further improved by better integration between different components such as summary generation and clustering components which inform each other, which we leave to future work.

[6] Performance for ground truth labels is lower than 100% due to noise in the human annotations, which is particularly prominent in Crosstask.

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A Script Generation

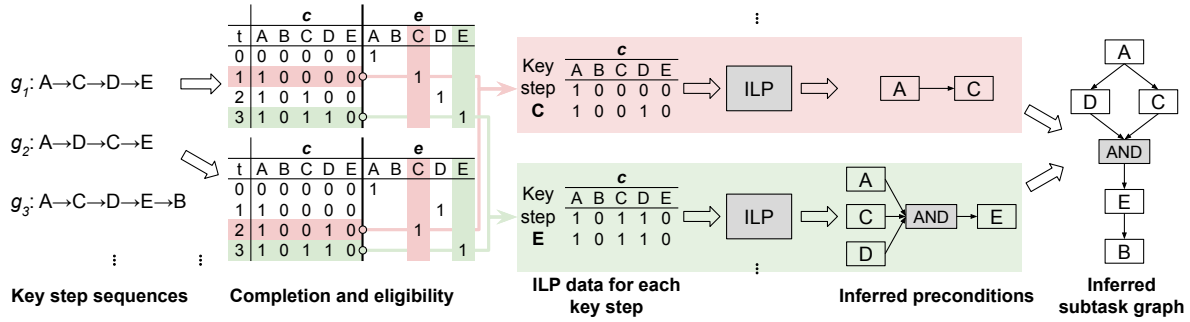


Figure 3: Procedure of predicting a script (or graph) from key step sequences.

We present details about the graph inference algorithm below.

Graph Representation Precondition describes the causal relationship between key steps relevant to a task and imposes a constraint on the order in which the key steps can be performed. Formally, the precondition is defined as a logical expression that combines the key steps using AND and OR logic operations, which means *all* or *any* of certain key steps should be completed, respectively. The precondition can be represented in disjunctive normal form (DNF) where multiple AND terms are combined with OR operations. These preconditions can be compactly represented in the form of a graph. The arguments of AND and OR operations in a precondition become the parents of corresponding AND and OR nodes in the graph, respectively. For example, in Figure 1, the precondition of step `give breaths` is OR(AND(`check breathing`, `open airway`)). Note that we omit AND and OR nodes with only one argument in the graph visualization for simplicity.

Graph Inference Given the set of known key steps $k_1, \ldots, k_m$ (*i.e.*, vertices of the graph), graph inference aims to infer the preconditions (*i.e.*, edges of the graph). We first define the notions of *completion* and *eligibility* of key steps at a given point in time while the task is being performed. We define the *completion* vector $\mathbf{c} \in \{0,1\}^m$ as a binary vector where $c[p] \in \{0,1\}; p \in \{1,\ldots,m\}$ represents whether key step k_p was performed in the past. Similarly we define the *eligibility* vector $\mathbf{e} \in \{0,1\}^m$ as a binary vector where $e[p]$ represents whether key step k_p is eligible to be performed (i.e., it's precondition is satisfied). The completion and eligibility status of key steps will change over time as different key steps are performed to complete the task. The precondition inference problem can be formulated as learning a function $\mathbf{e} = f_G(\mathbf{c})$. In other words, precondition inference amounts to predicting the eligibility status of a key step given the completion status of all key steps.

Given a key step sequence $h = (h^1, h^2, \ldots)$, we convert it into a sequence of completion and eligibility vectors $((\mathbf{c}^1, \mathbf{e}^1), (\mathbf{c}^2, \mathbf{e}^2), \ldots)$ as described next. We define the completion status $c^i[p]$ and eligibility status $e^i[p]$ of key step k_p as follows. If key step k_p was completed in the past (i.e., there exists $j \leq i$ s.t. $h^j \in k_p$), $c^i[p]$ is defined as 1 and 0 otherwise. On the other hand, key step k_p is considered eligible if $h^i \in k_p$ and it's eligibility is considered unknown otherwise. Cases where eligibility is unknown are ignored by the algorithm. See Figure 3 for an illustration of this conversion process.

Given $\{(\mathbf{c}^j, \mathbf{e}^j)\}$ as training data, Sohn et al. (2020); Anonymous (2022) proposed an Inductive Logic Programming (ILP) algorithm which finds the graph G that maximizes the data likelihood (Equation (1))

$$\widehat{G} = \arg\max_G \prod_j p(\mathbf{e}^j | \mathbf{c}^j, G) = \arg\max_G \sum_j \mathbb{I}[\mathbf{e}^j = f_G(\mathbf{c}^j)] \tag{1}$$

where $\mathbb{I}[\cdot]$ is the element-wise indicator function and f_G is the precondition function defined by the graph G, which predicts whether key steps are eligible from the key step completion vector $\mathbf{c}$. The precondition function f_G^p for key step k_p (i.e., $e[p] = f_G^p(\mathbf{c})$) is modeled as a binary decision tree where each branching node chooses the best key step to predict whether the key step k_p is eligible or not based on Gini impurity (Breiman, 1984). The precondition functions $f_G^1, \ldots, f_G^p$ learned for each key step k_p

induce a partial graph, which are consolidated to build the overall graph. See Figure 3 for an illustration of the process.

Graph Prediction Accuracy. *Accuracy* (Equation (2)) measures how often the output (*i.e.*, eligibility) of the predicted and the ground-truth preconditions agree (Sohn et al., 2020). f_G^{p*} is the ground-truth precondition of the key step k_p.

$$\text{Accuracy} = \frac{1}{m}\sum_{p=1}^{m} P\left(f_G^p(\mathbf{c}) = f_G^{p*}(\mathbf{c})\right) \tag{2}$$

B InstructGPT Summary Step Generations

We present *summary step sequences* generated by InstructGPT for the *setup chromecast* task below, conditioned on text transcripts from the dataset.

1. Go to Chromecast.com/setup
2. Connect Chromecast to HDMI port
3. Connect USB power cord to TV or power outlet
4. Open Google Home App
5. Follow on-screen instructions

1. Plug in the Chromecast to the TV.
2. Connect the Chromecast to the Wi-Fi network.
3. Use the Chromecast App to select what to cast.

1. Plug in the USB cable to the Chromecast.
2. Connect the Chromecast to the HDMI port on the TV.
3. Change the TV's input to the HDMI port that the Chromecast is connected to.
4. Download the Chromecast App.
5. Set up the Chromecast using the App.
6. Choose the Wi-Fi network.
7. Enter the Wi-Fi password.
8. Cast from the computer by using the Chromecast extension in Google Chrome.
9. Cast from the smartphone or tablet by using a compatible App.

We present *summary step sequences* generated by InstructGPT for the *change iphone battery* task below, conditioned on text transcripts from the dataset.

1. Turn off the phone
2. Remove the bottom screws
3. Lift up the screen
4. Remove the metal plate
5. Unclip the battery connector
6. Pry up the battery
7. Replace the battery
8. Replace the metal plate
9. Line up the screen
10. Snap the screen into place

1. Unscrew the two pentalobe screws beside the Lightning jack.
2. Use a mini suction cup and place it right above the home button.
3. Use a guitar pick to gently rock back and forth until the screen starts lifting.
4. Unscrew the battery cover and remove the shield.
5. Unplug the existing battery by going under the metal flap with a flat edge.
6. Remove the adhesive that keeps the battery in place.
7. Place the new battery in the chassis and plug it in.
8. Place the battery cover back on and screw it in.
9. Lock the top edge of the screen in place.
10. Screw the bottom screws in place.

1. Turn off the iPhone.
2. Remove the screws from the bottom of the phone.
3. Remove the screen from the phone.
4. Remove the battery connector.
5. Remove the adhesive strips from the old battery.
6. Attach the new adhesive strips to the new battery.
7. Place the new battery in the phone.
8. Reconnect the screen to the phone.
9. Replace the screws.
10. Turn on the phone.

All generated summary step sequences for all tasks can be found in the supplementary data folder.

C Key-steps identified

We show clusters/key steps identified by the clustering algorithm for the *setup chromecast* task below.

1.
   - Connect the Chromecast to the Wi-Fi network
   - Connect to the same Wi-Fi network
   - Enter Wi-Fi password to connect Chromecast to Wi-Fi network
   - Join the Chromecast to the Wi-Fi network
   - Connect the Chromecast device to the Wi-Fi network
   - Connect the Chromecast to a Wi-Fi network
   - Connect to the Chromecast's Wi-Fi network
   - Connect the Chromecast to your Wi-Fi network

2.
   - Plug in the Chromecast to the TV
   - Plug in the Chromecast device to the TV
   - Connect the Chromecast to the TV

3.
   - Download the Google Home app
   - Download the Google Home application
   - Download the Google Home App

4.
   - Plug Chromecast into HDMI port and USB port on TV
   - Plug Chromecast into HDMI port on TV
   - Plug Chromecast into HDMI port and USB port for power
   - Plug Chromecast into the HDMI port on your TV
   - Plug Chromecast into power and HDMI port on TV
   - Plug in the Chromecast device to the HDMI port and USB port for power

5.
   - Go to Chromecast.com/setup
   - Go to chromecast.com/setup
   - Go to chromecast.com/setup on an Android device
   - Go to google.com/chromecast/setup
   - Go to google.com/chromecast/setup in Chrome browser

6.
   - Follow on-screen instructions to set up Chromecast
   - Follow the instructions on the app to set up Chromecast
   - Follow the prompts to set up the Chromecast
   - Follow the prompts to set up Chromecast

7.
   - Install the Chromecast App on your phone or tablet
   - Open the Google Home app on your phone or tablet
   - Install the Chromecast app on the phone
   - Install the Chromecast App on your Android device
   - Install the Chromecast App on a computer or mobile device

8.
   - Download Chromecast App
   - Download Chromecast app
   - Download the Chromecast App
   - Download the Chromecast app

We show clusters/key steps identified by the clustering algorithm for the *change iphone battery* task below.

1.
- remove the bottom two screws from the phone
- Remove the screws at the bottom of the iphone
- Remove the two pentalobe screws at the bottom of the phone
- remove the two screws on the bottom of the iphone
- Remove the two screws at the bottom of the iPhone

2.
- remove battery
- remove the battery
- Remove battery
- Remove the battery
- Lift up the battery to remove it

3.
- put in the new battery
- Install the new battery
- stick the new battery in
- Insert the new battery
- Put in new battery

4.
- Pry up the frame of the screen with a pry tool
- use a suction cup and sharp blade to pry open the screen case
- use a suction cup and pry tool to remove the screen
- use a pry tool to snap the latches and remove the screen
- pry up very gently to separate the screen from the frame

5.
- Turn off the phone
- Turn off phone
- Turn off the iPhone

6.
- Remove the adhesive strips from the old battery
- remove the adhesive from underneath the battery
- use the fine tip curved tweezers to peel up the edges of the two adhesive strips at the bottom of the battery
- remove the adhesive strips holding the battery in place

7.
- Replace the screws
- replace screws
- Replace screws

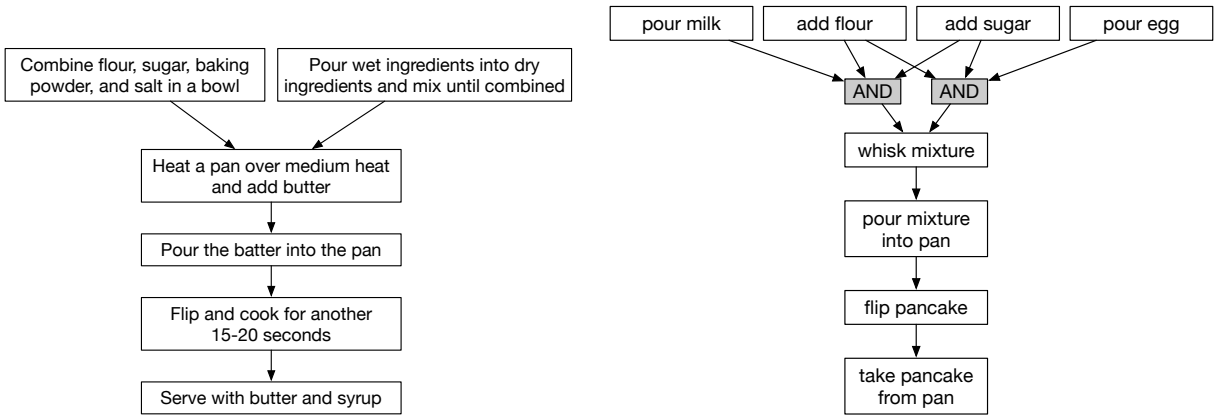
8.
- Lift up the screen with a suction cup
- use the suction cup to pull the screen up gently
- use a suction cup to pull up the screen
- Use a suction cup to slightly lift the screen
- Use a suction cup to apply upward pressure on the screen

9.
- Remove the metal bracket and the two screws holding down the battery cable
- remove the protective metal cover of the battery connector
- Remove the two screws in the battery connector cover
- remove the two screws on the shield that's covering the battery connector
- unscrew the metal bracket holding the battery connector in place

10.
- unscrew the four screws that cover the connectors for the screen
- remove the cover plate that covers the screen connectors
- Carefully dislodge the three connector tabs and set the screen aside
- remove the metal cover and gently pry off the connectors of the screen one by one
- Pull back the screen and remove the four screws securing the metal connector cover

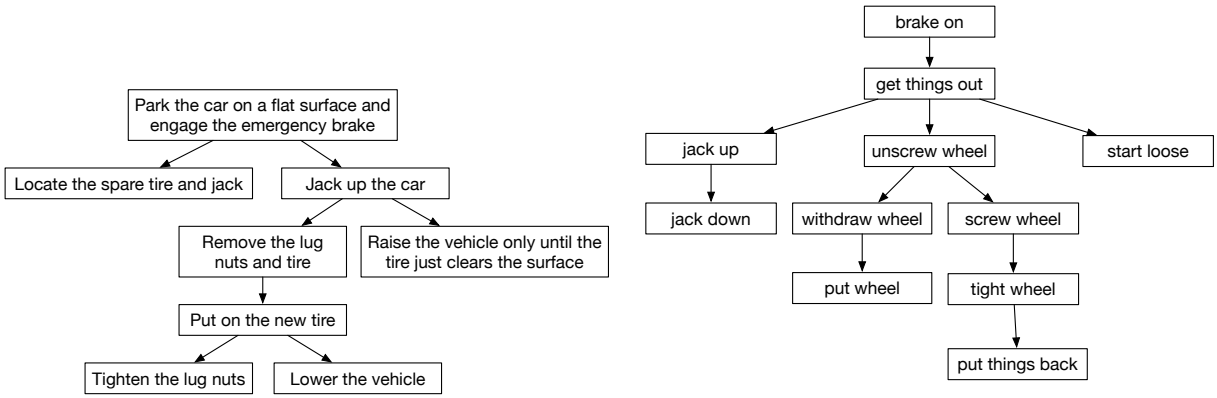
D Generated graphs

We include generated graphs for other Procel and Crosstask tasks below.



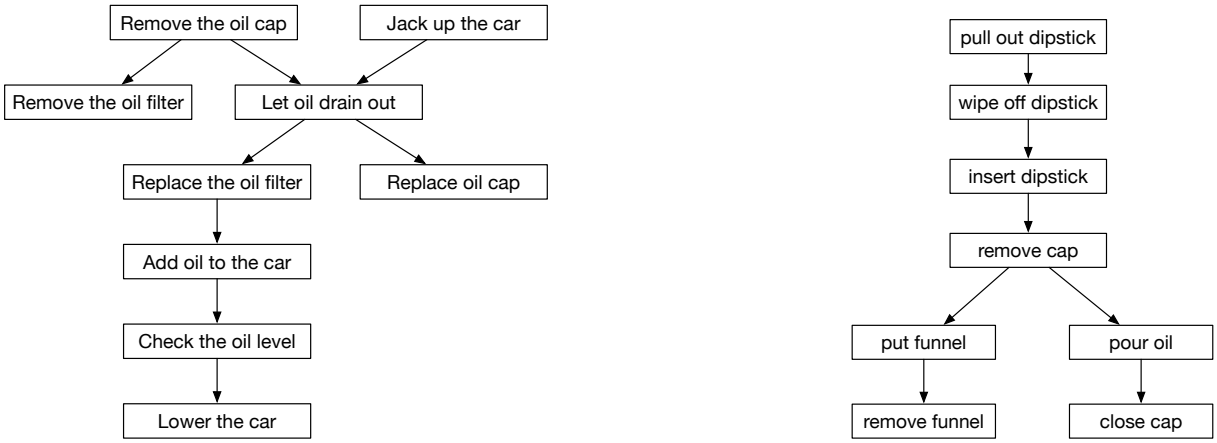
(a) Predicted graph (b) Ground truth grpah

Figure 4: Predicted (a) and ground truth (b) graphs for the *make pancakes* task.



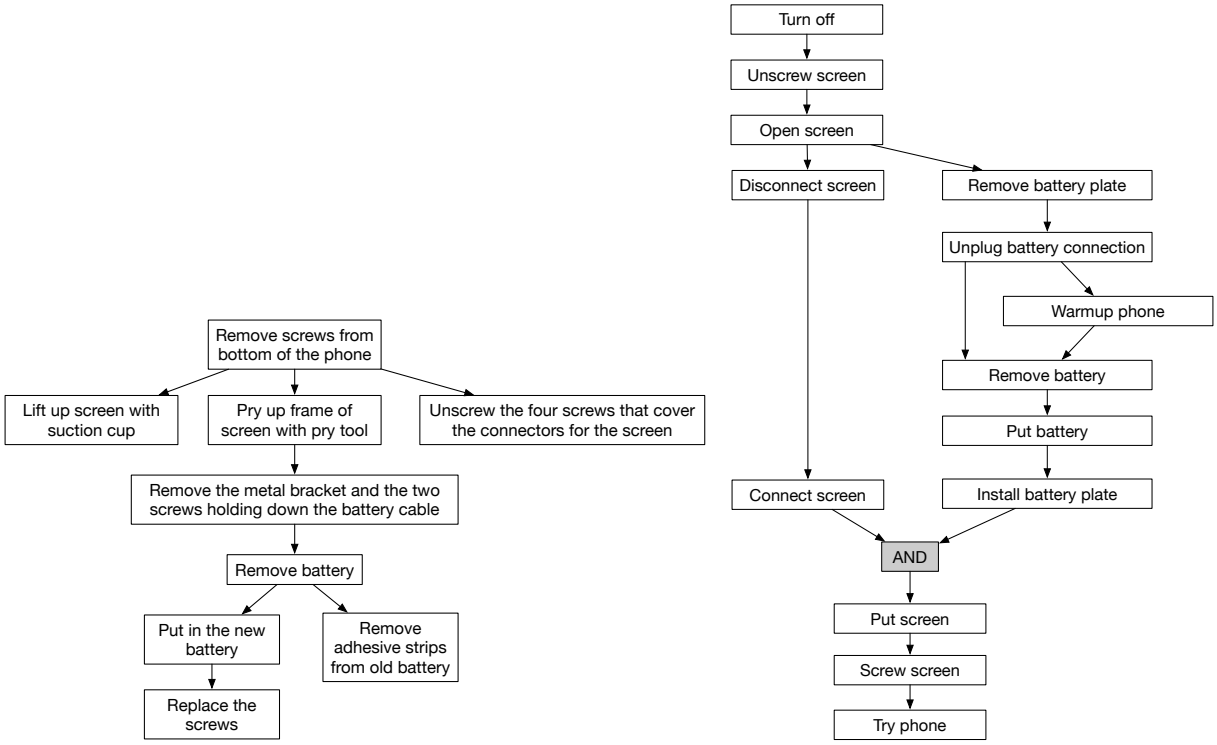
(a) Predicted graph (b) Ground truth grpah

Figure 5: Predicted (a) and ground truth (b) graphs for the *change tire* task.



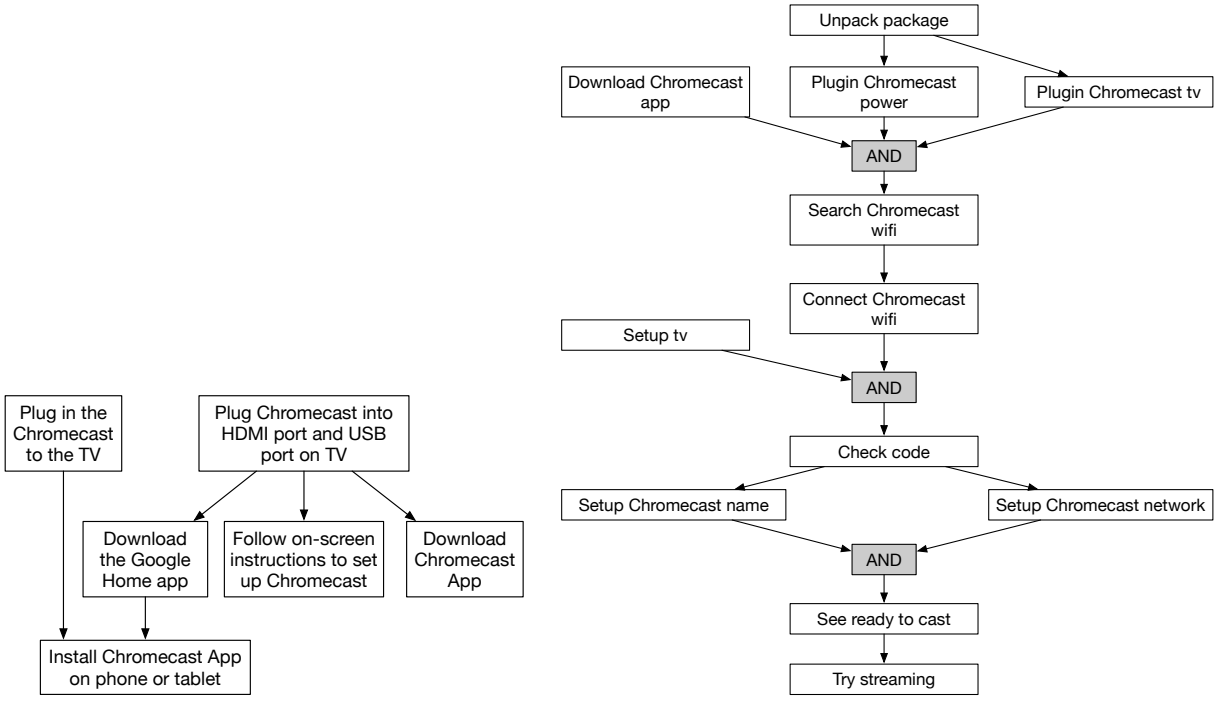
(a) Predicted graph (b) Ground truth grpah

Figure 6: Predicted (a) and ground truth (b) graphs for the *add oil to your car* task.



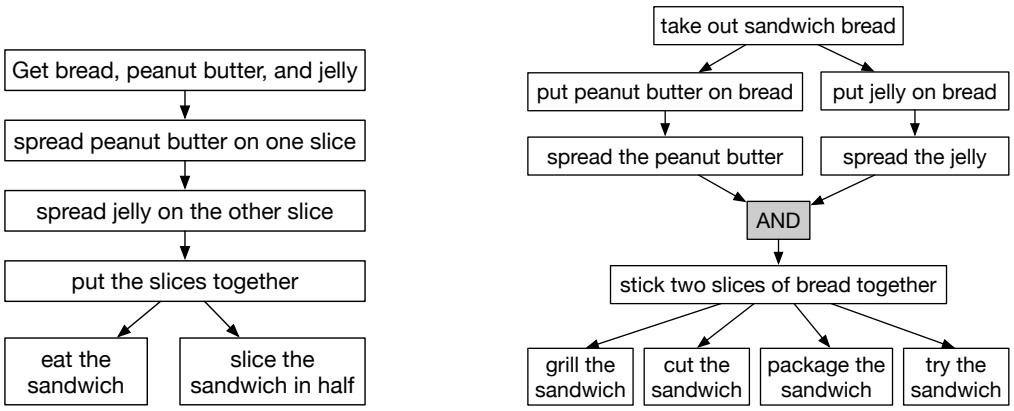
(a) Predicted graph (b) Ground truth grpah

Figure 7: Predicted (a) and ground truth (b) graphs for the *change iphone battery* task.



(a) Predicted graph (b) Ground truth grpah

Figure 8: Predicted (a) and ground truth (b) graphs for the *setup chromecast* task.



(a) Predicted graph

(b) Ground truth grpah

Figure 9: Predicted (a) and ground truth (b) graphs for the *make PBJ sandwich* task.

E Choice of Summary Step Sequence Generation Model

We perform an ablation to study the effect of the model used to generate summary step sequences from transcripts. We replace the InstructGPT model (Ouyang et al., 2022) with a FLAN-T5 model (Chung et al., 2022) and evaluate graph prediction performance. We find that InstructGPT consistently outperforms FLAN-T5 across all the tasks. In addition, we found that plain language models (not fine-tuned with instructions) struggled to produce usable summaries. This shows that models trained with instructions and human-preference data are better at producing scripts from transcripts compared to other forms of supervision such as language modeling and supervised multi-task training with NLP tasks.

Summary step generator	(a)	(b)	(c)	(d)	(e)	Avg
FLAN-T5 (Chung et al., 2022)	60.0	64.3	87.5	49.0	57.1	63.6
InstructGPT (Ouyang et al., 2022)	**76.2**	**80.4**	**90.6**	**51.0**	**62.5**	**71.1**

Table 2: Graph prediction accuracy on the Procel dataset when different models are used for summary step generation. The tasks are (a) make PBJ sandwich (b) change iphone battery (c) perform CPR (d) set up chromecast (e) tie tie.

F Choice of Ranking Language Model

We perform an ablation to study to understand the impact of the choice of language model for the ranking process in Section 2.4. We present the average performance on tasks in the Procel dataset with different language model choices in Table 3. First, we find that performance does not degrade much when switching to a smaller model in the GPT2 family. Second, we notice that scale alone does not guarantee better ranking performance as the larger GPT-J model (Wang and Komatsuzaki, 2021) is inferior to the GPT2 models. These findings suggest that the choice of pre-training data influences the script knowledge present in a model and can be more important than model scale.

Language Model	Parameter Count	Performance
GPT2-Medium (Radford et al., 2019)	345M	70.96
GPT2-XL (Radford et al., 2019)	1.5B	**72.14**
GPT-J (Wang and Komatsuzaki, 2021)	6B	68.80

Table 3: Ranking performance of different Language Models on the Procel dataset.