



Investigate Procedure Events in *Multimodal* Fashion

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Introduction

- Procedural events: a set of steps to accomplish a certain goal.
- Represented as *scripts/schema* that human uses to perform everyday tasks.

Schema of Change a Tire

- Find a safe place.
- Park the car.
- Take out the spare tire.
- Raise the jack.
- Loosen the nuts.
-



Flat tire during my trip in CA

Introduction

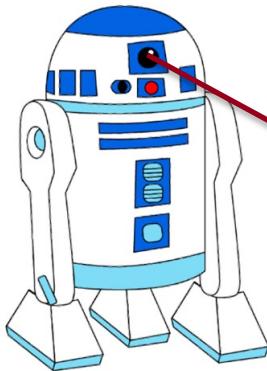
- Scripts for natural language understanding (Schank and Abelson, 1977)
- Supervised learning for corpora, e.g., Framenet (Baker et al., 1998)
- Narrative Schemas and Event Chains (Chambers and Jurafsky, 2007, 2008, 2009)

Events	Roles
A search B	A = <i>Police</i>
A arrest B	B = <i>Suspect</i>
B plead C	C = <i>Plea</i>
D acquit B	D = <i>Jury</i>
D convict B	
D sentence B	

- Goal-Step Relations (Lyu et al., 2020)
 - Goal-Step Inference
 - Step Ordering
- | | |
|---------------------------|-------------------------------|
| Goal: Prevent Coronavirus | Goal: Clean Silver |
| A. wash your hands | A. dry the silver |
| B. wash your cat | B. handwash the silver |
| C. clap your hands | |
| D. eat your protein | |

Motivation

- Past work mostly examined the procedure events for text.



Make Tea?
Make Coffee?
Cook Noodles?
Recommendations

Motivation

Schema of *Get a slice of cake*:

take the cake out of the box → cut a slice → put it on a plate → take the plate to the user

Reporting Bias (Gordon and Van Durme, 2013)



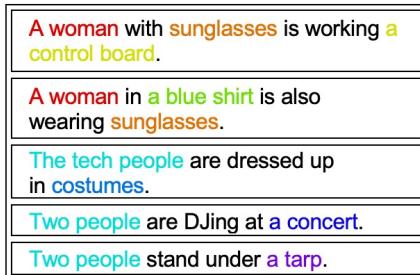
Visual Goal-Step Inference using wikiHow

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Introduction

- Learning goal-step relations in multimodal fashion.
- We propose the Visual Goal-Step Inference (VGSI)
 - Given given a textual goal.
 - Infer which image represents a plausible step.
- More challenging than text-image matching
 - Text and objects are not closely matched



Caption-based image-text task

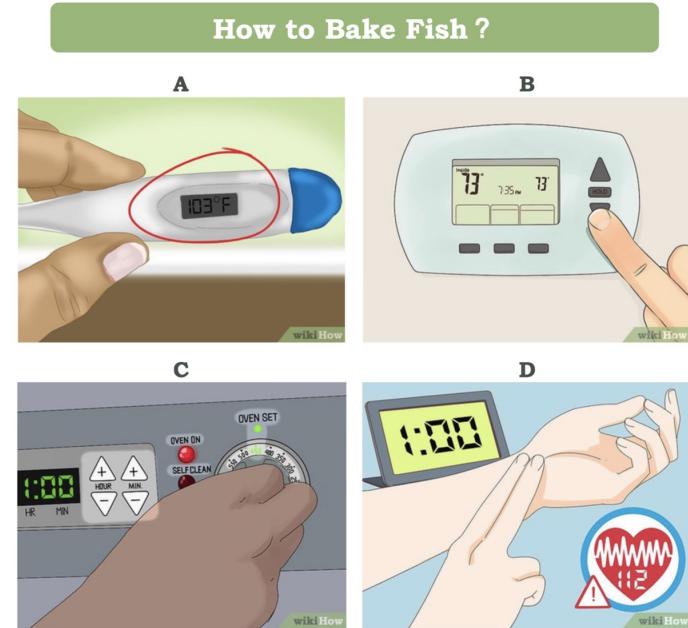


Figure 1: An example Visual Goal-Step Inference Task: given a text goal (*bake fish*), select the image (C) that represents a step towards that goal.

Dataset

- Harvested from wikiHow
- Goal – Method – Step structure
- The corpus consists
 - 53,189 wikiHow articles across various categories
 - 155,265 methods, 772,294 steps/images

Category	Goals	Methods	Steps	Images
Health	7.8k	19.1k	97.5k	111.8k
Home and Garden	5.9k	16.0k	82.9k	85.4k
Education & Communications	4.7k	12.4k	61.2k	66.1k
Food & Entertaining	4.6k	11.6k	62.0k	69.0k
Finance & Business	4.4k	11.8k	59.3k	66.8k
Pets & Animals	3.5k	9.5k	45.3k	48.0k
Personal Care & Style	3.4k	9.0k	46.1k	48.9k
Hobbies & Crafts	2.8k	7.5k	40.9k	42.7k
Computers & Electronics	2.6k	6.1k	31.5k	36.2k
Arts & Entertainment	2.5k	6.8k	35.4k	37.2k
Total	53.2k	155.3k	772.3k	772.3k

Table 1: Number of goals, methods, steps and images in the top 10 wikiHow categories.

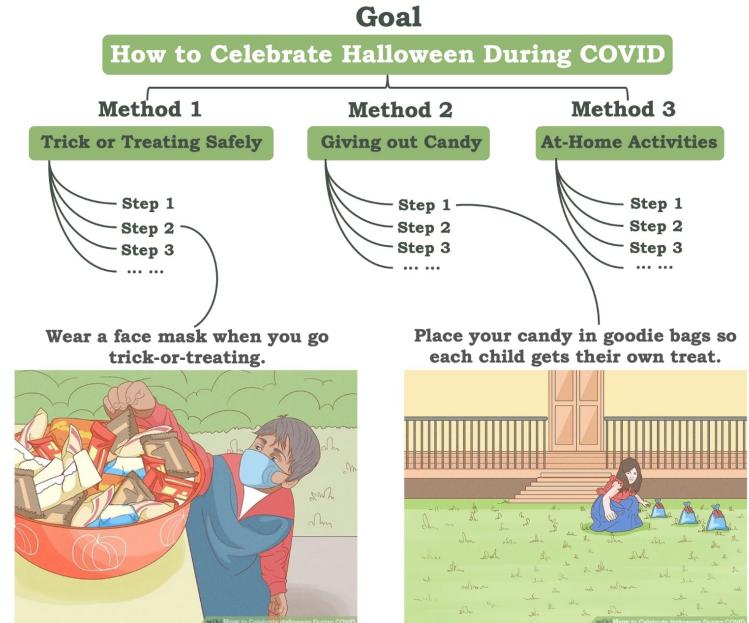


Figure 2: Hierarchical multimodality of wikiHow.

Sampling Strategies

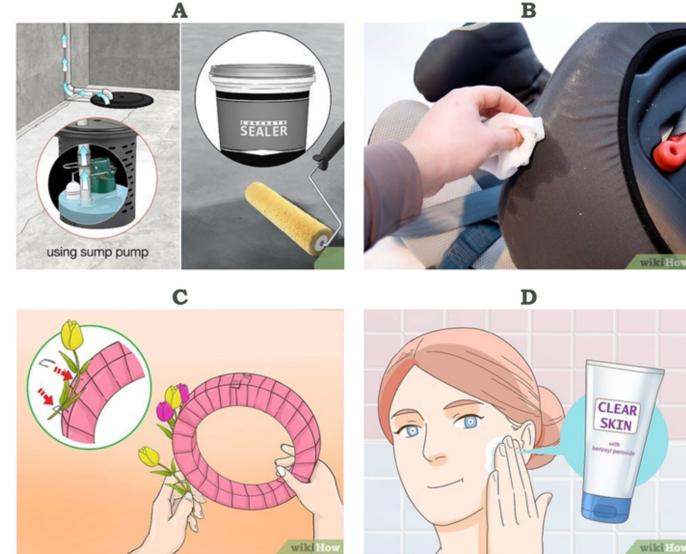
- Random Sampling

(A) Random Sampling



(A.1) Correct Answer is **B**

How to Prevent Millipedes ?



(A.2) Correct Answer is **A**

Sampling Strategies

- Similarity Sampling

(B) Similarity Sampling

How to Dry Jeans ?

A



B



C



D



How to Do a Man Bun ?

A



B



C



D



(B.1) Correct Answer is **B**

(B.2) Correct Answer is **C**

Sampling Strategies

- Category Sampling

(C) Category Sampling



(C.1) Correct Answer is **A**

(C.2) Correct Answer is **D**

Experiments

- Problem Formulation:
 - Input: a high-level goal G , an Image I
 - The model outputs the matching score:

$$\text{match}(G, I) = F(X_G, X_I) \quad (1)$$

- Baseline Models:
 - **DeViSE**
 - **Similarity Network**
 - **Triplet Network**
 - **LXMERT (transformer-based)**
- Human Annotation

Results

Model	Sampling Strategy (Test Size)		
	Random (153,961)	Similarity (153,770)	Category (153,961)
Random	.2500	.2500	.2500
DeViSE	.6719	.3364	.4558
Similarity Net	.6895	.6226	.4983
LXMERT	.7175	.4259	.2886
Triplet Net (GloVe)	.7251	.7450	.5307
Triplet Net (BERT)	.7280 _{-13.8%}	.7494 _{-8.77%}	.5360 _{-29.0%}
Human	.8450	.8214	.7550

Table 2: Accuracy of SOTA models on the wikiHow VGSI test set with different sampling strategies (sample size is shown in parentheses).

Results

- The knowledge learned from wikiHow can be transferred to other datasets.

		Sampling Strategy		
PT-Data	FT?	Random	Similarity	Category
-	✓	.6005	.6096	.4434
	✗	.4837	.5398	.3856
Flickr30K	✓	.6207	.6408	.4740
	✗	.5099	.5715	.3958
MSCOCO	✓	.6340	.6640	.4794
	✗	.5067	.5161	.3978
COIN	✓	.6170	.6343	.4638
	✗	.6556	.6754	.4750
wikiHow	✓	.6855	.7249	.5143
Human	-	.8300	.7858	.7550

Table 4: Transfer performance (4-way multiple choice accuracy) on Howto100m. FT results are obtained by fine-tuning the model on the full training set.

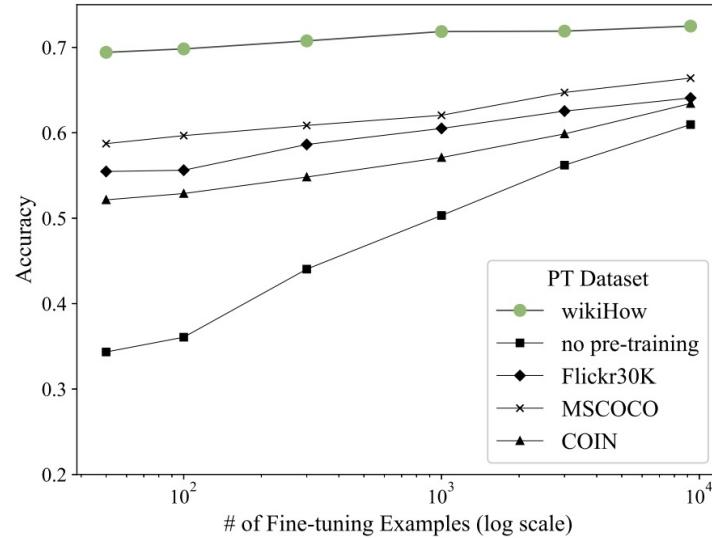


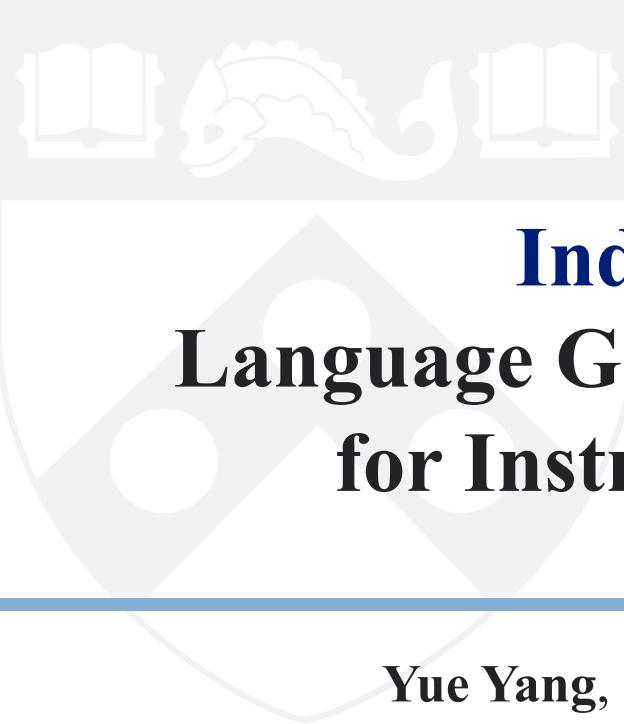
Figure 5: Transfer performance on Howto100m (similarity sampling) with different pre-training datasets vs. the number of training examples.

Conclusion

- We propose the novel Visual Goal-Step Inference task (VGSI), a multimodal challenge for reasoning over procedural events.
- We construct a dataset from wikiHow and show that SOTA models struggle on it.
- The knowledge harvested from our dataset could be transferred to other datasets.
- The multimodal representation learned from VGSI has strong potential to be useful for NLP applications such as multimodal dialog systems, multimodal schema induction systems.

Dataset and code are available at

<https://github.com/YueYANG1996/wikiHow-VGSI>



Induce, Edit, Retrieve: **Language Grounded Multimodal Schema** **for Instructional Video Retrieval**

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Motivation

- *Schema*: a set of rules people use to perform everyday tasks.
- Schema can be *generalized*.
- When facing new tasks, people use *prior* knowledge. (Chen et al., 2004)



Motivation

- *Problems on current Schema Induction System*
 - Use text only (reporting bias)
 - Rely on labeled data
 - Small scale
 - Multimodal downstream tasks
- *Can Vision adopt such reasoning approach?*
 - Induce schemata from visual signals.
 - Generalize schemata for larger scale.
 - Use schemata to improve multimodal tasks.

IER Overview

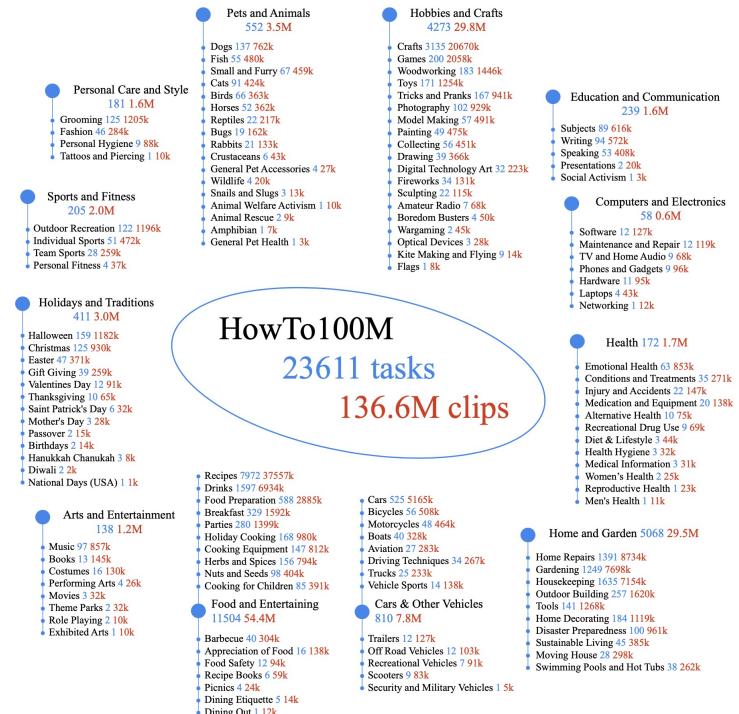
- Our Induce, Edit, Retrieve (IER) system:
 - Induce:
 - Input: A task name, a set of related videos
 - Output: A set of sentences as the schema
 - Edit
 - Given an unseen task
 - Use language models to modify schema
 - Retrieve
 - Improve video retrieval using schema



Figure 1. An example from our IER system, which first induces a schema for *Bake Chicken* using a set of videos. Then it edits the steps in the schema to adapt to the unseen task *Bake Fish* (the tokens that have been edited are highlighted). Finally, IER relies on the edited schema to help retrieve videos for *Bake Fish*.

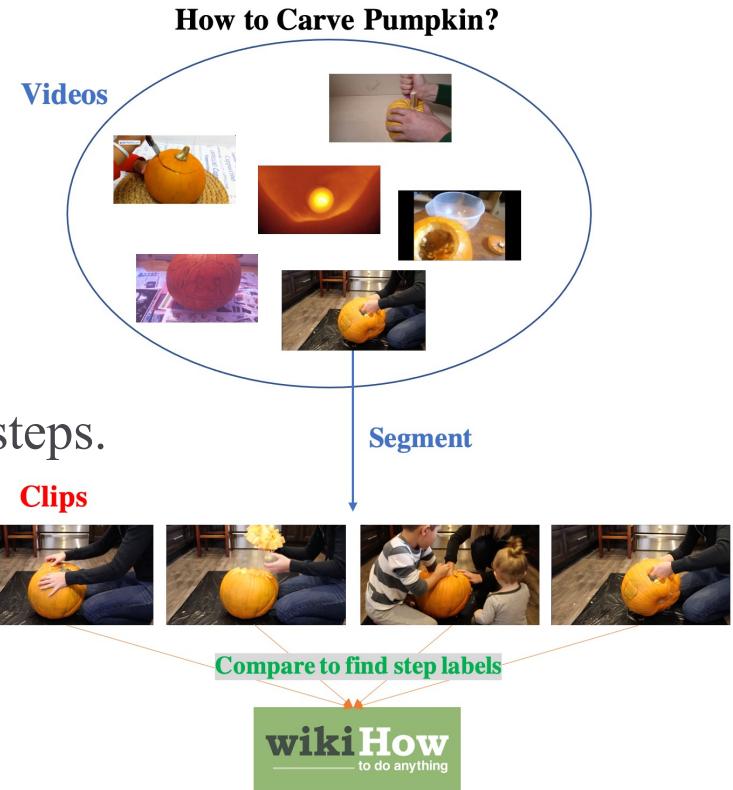
Schema Induction

- Generate schemata for a set of tasks based on their associated videos
 - Input: A bag of videos
 - Out: A bag of step descriptions
- Learning Data – Howto100M (Miech et al., 2019)
 - 136 M video clips from 1.22M instructional videos
 - 23K tasks, directly from wikiHow
 - Focus on visual tasks only
 - Retrieve videos from YouTube



Schema Induction

- How to convert video to text?
 - Captioning? Transcripts? Template?
- Use human written steps in wikiHow!
 - 1M steps from 110k articles on everyday tasks
- Use pretrained video-text model to retrieve steps.
 - MIL-NCE (Miech et al., 2019)
 - (Clip, Step) matching score
 - Pair every video segment with all 1M steps
 - Sort steps based on the matching score



Schema Induction



Task: Make Tea

Retrieved step label: Strain the tea through a filter and pour it into cups.



Task: Carve Pumpkin

Retrieved step label: Scoop the seeds out of your pumpkin with a large serving spoon.



Task: Change a Tire

Retrieved step label: Jack the car up so that you can fit, comfortably, underneath the car.

Schema Induction

- For each video segment, we select top-30 steps.
- We further sort these steps based on the average matching score across all videos.
- The top-100 steps are selected.
- Hierarchical clustering to remove paraphrases
- On average, 25.1 steps per task



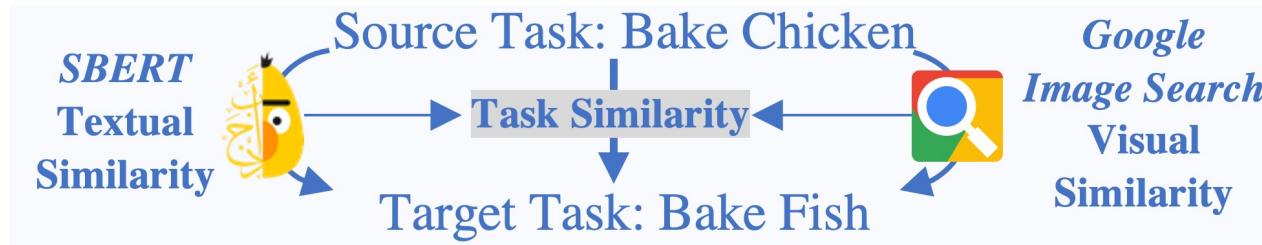
Top-10 Retrieved Steps	Similarity Score
Carve a scary pumpkin and place it outside.	13.25
Mark the pumpkin drill holes .	12.15
Carve a face in the jelly , similar to a pumpkin face.	11.93
Cut a hole in the back of the pumpkin large to fit your hand through.	11.83
Carve a pumpkin for Halloween .	11.50
Carve around the nose with a knife to finish outlining it.	11.36
Place the Cylon pumpkin on display.	11.35
Carve the pumpkin as shown in this image.	10.91
Have some pumpkin flesh and seeds!	10.29
Cut the pumpkin in half , lengthwise.	10.08

Schema Induction

How to Stain Cabinets	How to Use a Drill Safely	How to Replace Shocks
<ul style="list-style-type: none">• Glaze the doors using the same process you did with the cabinets.• Choose a whitewash wood stain.• Paint dated cabinets and dark walls.• Finish the cabinets with a top coat.• Apply glaze to a section of one cabinet door or drawer.• Opt for semi-custom cabinets for a midrange budget option with more features.• Prime the cabinets with white primer paint.• Put a lazy susan in your cabinets.• Choose an appropriate urethane finish for the door.• Apply the dye to the poplar with a rag.	<ul style="list-style-type: none">• Set the plunge depth for the drill.• Put on safety glasses before you start drilling.• Secure the cord grip by installing the grub screw with an Allen wrench.• Wear safety goggles and a dust mask while drilling.• Locate the chuck at the end of the drill.• Drill your team with simulated data breaches.• Drill through the tile slowly.• Set up your guide rail for cutting with a plunge saw.• Complete routing and other machining before ebonizing.• Wear the proper safety gear when sawing and drilling into wood.	<ul style="list-style-type: none">• Visually inspect your strut mounts or shock towers.• Call the bank's toll-free customer service number.• Sign up for an email service.• Drop it off at an auto repair or auto parts shop.• Replace each hubcap.• Inspect your wheel wells and bumpers.• Examine the lug nuts.• Take your vehicle to a reputable repair shop for diagnosis and repairs.• Keep your tires aired up.• Loosen the bleeder.

Schema Editing

- Given an unseen task without videos, edit existing schema.
- Find the most similar task in the schema library



- Textual Similarity = cosine similarity of SBERT embeddings
- Visual Similarity (Google Image Search)
- Task Similarity = $\max(\text{Textual Similarity}, \text{Visual Similarity})$

Schema Editing – Object Replacement

- Editing Module 1: Object Replacement
- Every task has a main object, e.g., “chicken” of “Bake Chicken”
- Use POS tagger to find the 1st occurred noun as main object
- Replace the objects in all steps

Object Replacement
Cook Ham $\xrightarrow{0.86}$ Cook Lamb Put the ham in the oven. \downarrow Put the lamb in the oven.
Clean a Guitar $\xrightarrow{0.84}$ Build a Violin Use a polish for particularly dirty guitars . \downarrow Use a polish for particularly dirty violins .
Trap a Rat $\xrightarrow{0.84}$ Trap a Rabbit Bait and set snap rat traps. \downarrow Bait and set snap rabbit traps.

Schema Editing – Step Deletion

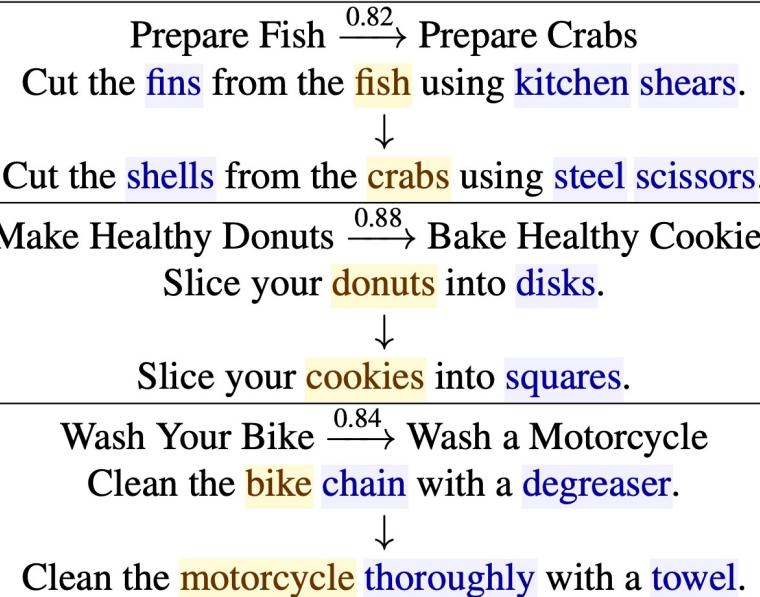
- Editing Module 2: **Step Deletion**
- Delete the steps no longer suitable for the new target task.
- “Insert a roasting thermometer into the thigh” of “Bake Chicken” ~~X~~ “Bake Fish”
- Sentence BERT pretrained on question-answer pairs.
- Compute the score of (task, step).
- if (source task, step) >> (target task, step)
 delete, otherwise include

Step Deletion
Transplant a Young Tree $\xrightarrow{0.89}$ Remove a Tree Fill your pot with a balanced fertilizer. \downarrow delete Fill your pot with a balanced fertilizer.
Fix a Toilet $\xrightarrow{0.85}$ Remove a Toilet Test out the new flapper. \downarrow delete Test out the new flapper.
Brush a Cat $\xrightarrow{0.87}$ Brush a Long Haired Dog Comb and groom your pet. \downarrow include Comb and groom your pet.

Schema Editing – Token Replacement

- Editing Module 3: **Token Replacement**
- Use *masked language model* to replace the token with the lowest probability.
 - “Season the **drumstick**” in “Bake Chicken”
 - Mask the token “Season the <mask>”.
- Use a prompt: How to [TASK]? [STEP]
 - How to Bake Fish? “Season the <mask>”.
- Predict a new token from vocabulary
 - <mask> → fish, “Season the fish”

Token Replacement



Schema Guided Video Retrieval

- Query: Task Name (short) Retrieve **long multi-minute** videos
- Global Matching (use task name only)
- Step Aggregation (use schemata to expand task name)

Use the task name "Bake Fish" as Query



Wash the fish



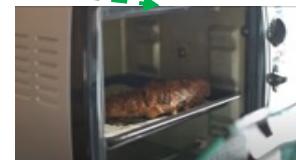
Sprinkle the sauce on the fish



With Schema

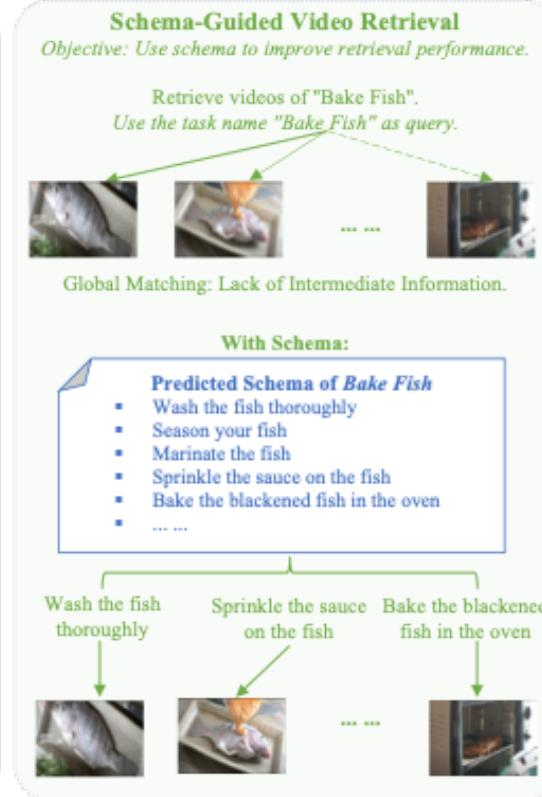
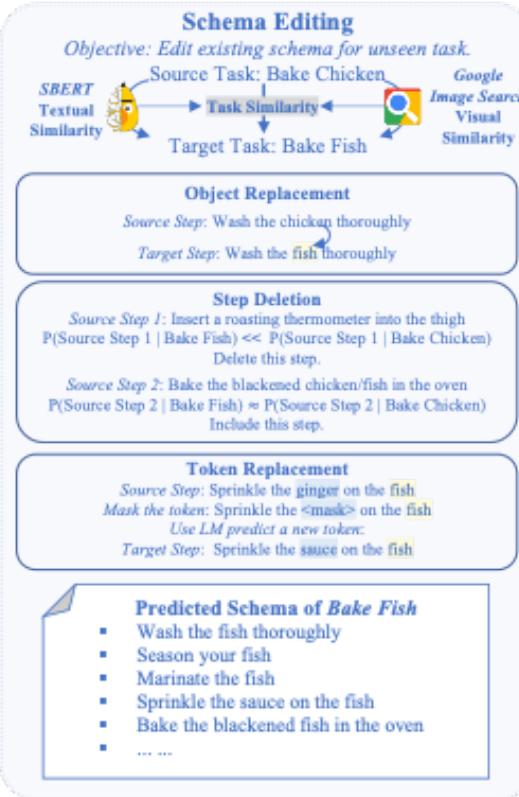
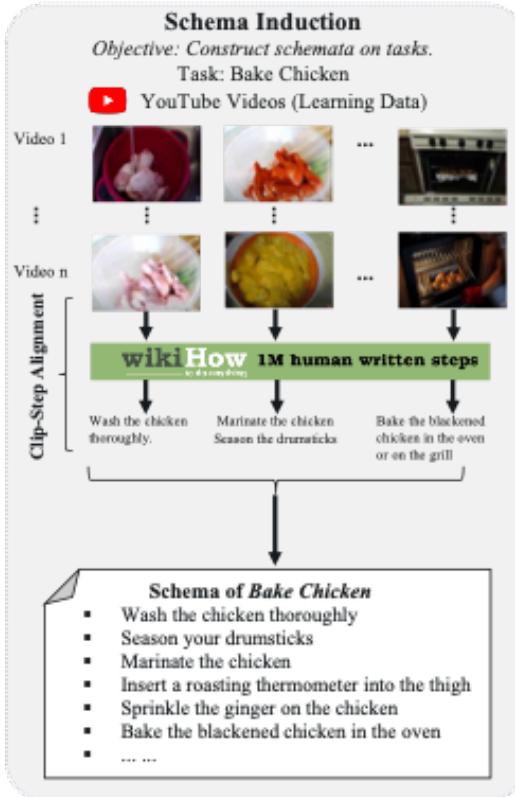


Preheat the oven.



Bake the blackened fish in the oven

IER Review

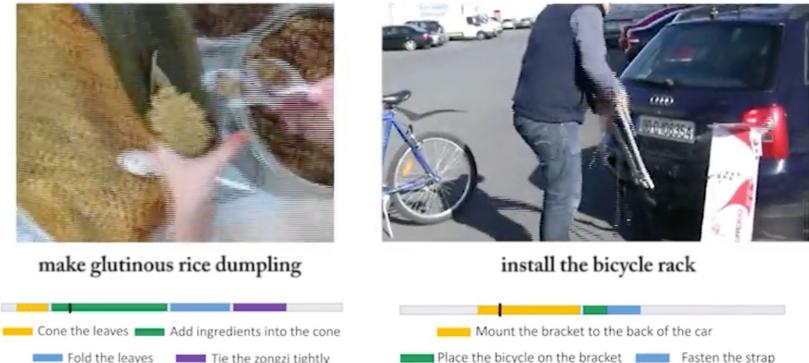
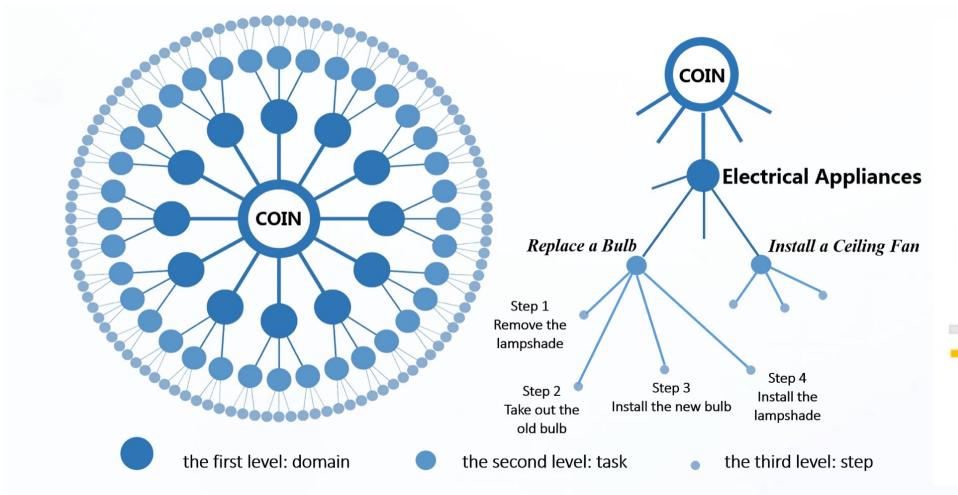


Experiments - Datasets

- **Howto-GEN** (a new split of Howto100M)
 - Select the task names with exact one noun
 - 3365 tasks, 2,184 unique main objects
 - Random select 500 tasks for training, 500 for validation, 2365 for test.
 - 1,088 unseen main objects in the test set
 - Train: Peel Tomato
 - Test: Peel Kiwi, Peel Banana, Peel Onion
 - 5 videos for each test task for retrieval
 - Pair with 2495 randomly selected distracting videos

Experiments - Datasets

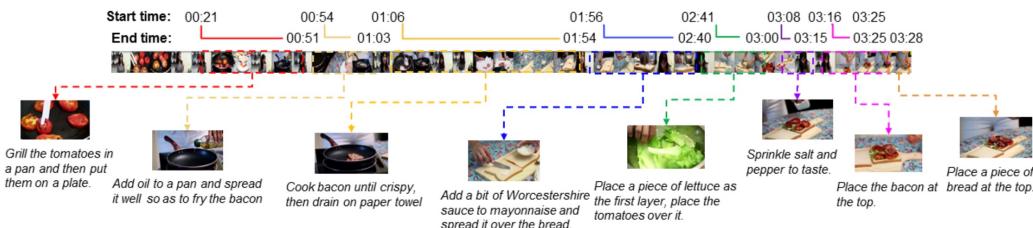
- COIN (COmprehensive INstructional video analysis)
 - 180 tasks, 11,827 videos
 - Unseen tasks, e.g., “Blow Sugar”, “Make Youtiao”, etc.
 - 5 test videos for each tasks, 900 in total



For each video, we annotate a series of steps
with their temporal boundaries

Experiments - Datasets

- Youcook2
 - 89 recipes – tasks, 2,000 long videos
 - A retrieval pool of 436 videos (no overlap with Howto100M)



Dataset	# of tasks	# of videos	Avg. video length (s)
Howto-GEN	2,365	11,825	392.9
COIN	180	900	143.2
Youcook2	89	436	310.9

Table 2. Statistics of the evaluation datasets (test set).

Experiments - Baselines

Task: Make Tea

- **Generation Models**
 - T5 (Lyu et al. 2021)
 - GPT-2-large
 - GPT-3: Zero-shot generation
 - How to [Task Name]? Give me several steps.
- **GOSC** (Lyu et al. 2021)
 - Goal-Oriented Script Construction
 - Step Inference model
 - Given the input task name
 - Gather the set of desired steps from wikiHow
- **Oracle**
 - Howto-GEN (from wikiHow)
 - COIN/Youcook2 (Human annotation)

GPT3

- Steep tea leaves for 3-5 minutes.
- Pour tea into cups.
- Pour boiling water into the teapot.
- Put tea leaves into a teapot.
- Add sugar or honey to taste.

GOSC

- Find a tea you enjoy.
- Submerge tea leaves in boiling water.
- Select the tea varieties.
- Steep tea leaves in hot water
- Build a tea garden.

Oracle

- add some ingredients to the tea
- prepare and boil water
- pour the tea into the vessel
- prepare and add the tea
- heat the teapot and wash the cup
- add some water to the tea

Results

Method	Howto-GEN					COIN					Youcook2					
	P@1↑	R@5↑	R@10↑	Med r↓	MRR↑	P@1↑	R@5↑	R@10↑	Med r↓	MRR↑	P@1↑	R@5↑	R@10↑	Med r↓	MRR↑	
MIL-NCE [31]	45.2	31.0	43.1	15.0	.198	48.3	37.1	52.8	9.5	.227	27.0	18.2	26.5	32.0	.126	
Step Aggregation	T5 [30]	44.0	29.9	41.0	19.0	.190	46.1	35.3	50.7	10.0	.219	21.3	16.0	24.7	61.5	.108
	GPT-2 [39]	46.0	31.5	43.3	16.0	.200	48.9	39.2	53.4	8.0	.233	31.5	19.0	27.3	44.5	.130
	GPT-3 [2]	49.3	33.3	45.7	13.0	.211	53.3	42.1	59.0	8.0	.252	37.1	22.4	34.6	27.0	.160
	GOSC [30]	54.7	37.0	49.8	11.0	.231	53.9	41.6	55.1	8.0	.248	30.3	20.7	34.8	28.0	.146
	wikiHow	51.9	35.4	47.8	11.0	.222	53.9	40.8	56.1	7.0	.246	31.5	21.0	34.2	24.5	.149
	IER (Ours)	54.4	37.3	50.1	10.0	.231	57.2	42.2	57.8	7.0	.256	41.6	25.8	38.8	20.0	.175
	IER ³ (Ours)	55.0	37.4	50.6	10.0	.234	56.1	42.3	59.1	8.0	.258	40.4	25.1	38.8	20.0	.172
	Oracle	56.5	38.0	50.8	10.0	.237	60.0	43.4	59.3	7.0	.262	52.8	33.5	47.1	14.0	.215

Table 3. Retrieval performance on Howto-GEN, COIN and Youcook2. Baselines include retrievals based on global matching, aggregation of steps generated from state-of-the-art language models, goal-oriented script construction (GOSC), and wikiHow. The Oracle upper bound contains human-written step labels for each task. Observe that our **IER** systems outperform the baselines across all metrics.

Results

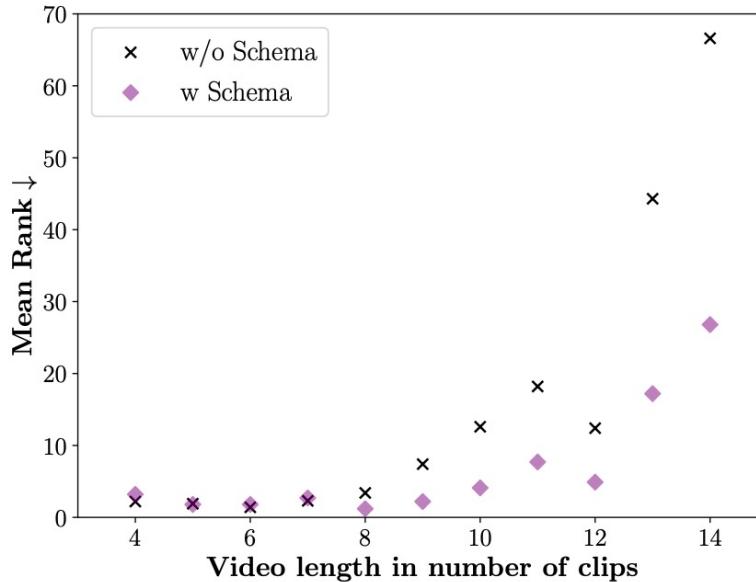


Figure 3. Retrieval performance by video length (in the number of clips). We group the test videos of Youcook2 by the number of clips per video and compute the mean rank for each group.

IER helps more for longer videos

Editing Module Ablations

	Method	P@1↑	R@5↑	R@10↑	Med r↓	MRR↑
Howto-GEN	full	54.4	37.3	50.1	10.0	.231
	– mask	53.7	36.3	49.3	11.0	.229
	– deletion	53.6	36.9	49.8	11.0	.230
	– replacement	<u>51.5</u>	<u>34.9</u>	<u>47.3</u>	<u>12.0</u>	.220
	– all	<u>45.5</u>	<u>31.0</u>	<u>43.1</u>	<u>15.0</u>	.199
COIN	full	57.2	42.2	57.8	7.0	.256
	– mask	53.9	42.3	58.3	7.0	.257
	– deletion	58.3	42.0	58.0	7.0	.258
	– replacement	<u>53.8</u>	<u>41.0</u>	59.2	<u>7.5</u>	.251
	– all	54.4	39.6	<u>53.7</u>	8.0	.246
Youcook2	full	41.6	25.8	38.8	20.0	.175
	– mask	<u>40.4</u>	<u>25.4</u>	39.3	20.0	.173
	– deletion	41.6	26.0	39.1	<u>21.0</u>	.175
	– replacement	40.4	25.8	<u>38.5</u>	20.0	.173
	– all	40.4	26.0	39.9	21.0	.174

Table 4. Ablation study on editing modules. “full” represents using all three modules and “– all” denotes removing all three modules. “– mask”, “– deletion” and “– replacement” are short for removing “Token Replacement”, “Step Deletion” and “Object Replacement” respectively. The numbers with underline are the ones lower than “full”. The highest number of each metric is **bold**.

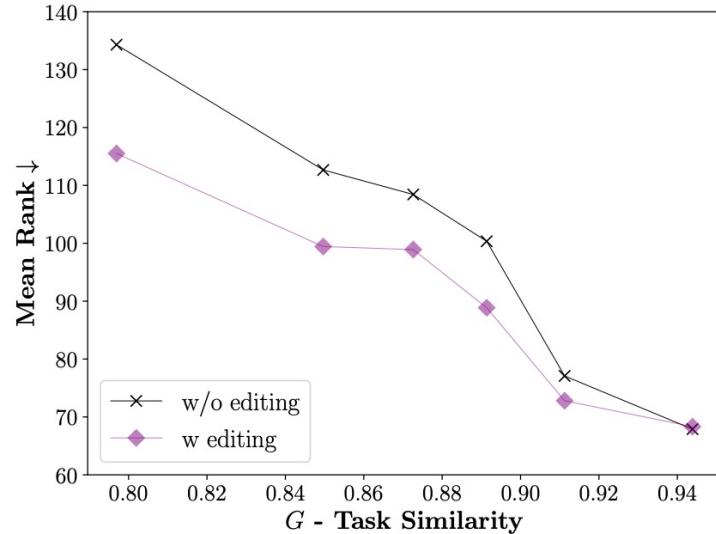


Figure 4. Retrieval performance by task similarity. We sort the test tasks of Howto-GEN based on their task similarity (G) and compute their mean rank for every batch of 400 tasks.

Editing helps more when task similarity is low.

Schemata Transfer

- Schemata can be reused by different video-text model
- Use CLIP (Radford et al., 2021) as the video-text matching function
 - 400 million (image, text) pairs
 - Global Matching
 - Step Aggregation with schemata
- Schemata are transferable.

Model	P@1↑	R@5↑	R@10↑	Med r↓	MRR↑
MIL-NCE	48.3	37.1	52.8	9.5	.227
+schema	57.2	42.2	57.8	7.0	.256
CLIP [38]	58.9	44.9	58.8	6.0	.264
+schema	65.0	47.4	60.8	5.5	.282

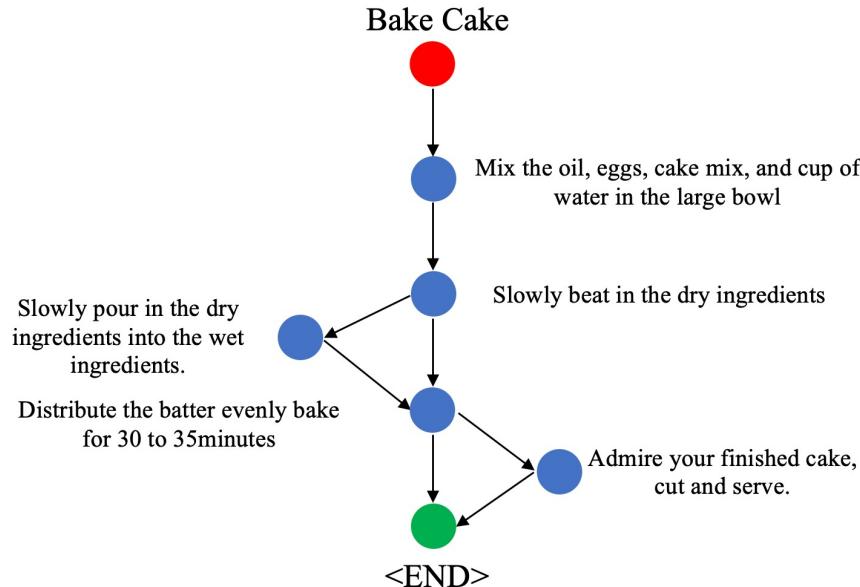
Table 5. Retrieval performance on COIN using MIL-NCE and CLIP as the matching functions. +schema represents using schema induced by IER (MIL-NCE as matching function) for retrieval.

Conclusion & Future Work

- We propose a schema induction and generalization system that improves instructional video retrieval performance.
- We demonstrate that the induced schemata benefit video retrieval on unseen tasks, and our IER system outperforms other methods.
- In the future, we plan to investigate the structure of our schemata.

Conclusion & Future Work

- Temporal order in schema graph



- Other schemata applications
 - Video Anticipation
 - Task Identification
- Other aspects of schema
 - argument, duration, etc.
- Schema induction on other types of videos
 - News, human activities
 - Ego4D



Thank you!