Feb 2023 AAAI Tutorials Knowledge-Driven Vision-Language Pretraining



# **Procedural Knowledge**

Knowledge-Driven Vision-Language Pretraining (Part IV)

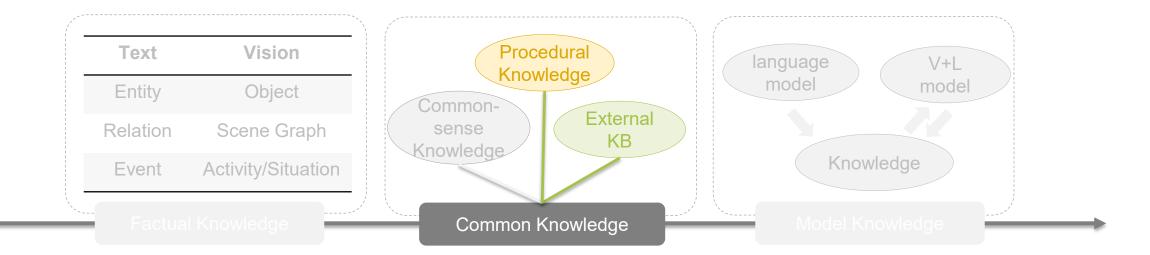
Xudong Lin Columbia University xudong.lin@columbia.edu







Learning patterns of procedure with human-curated patterns and data.

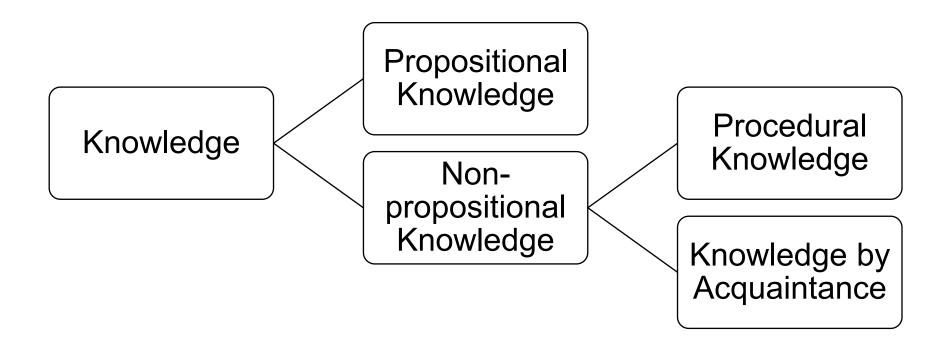


### Agenda

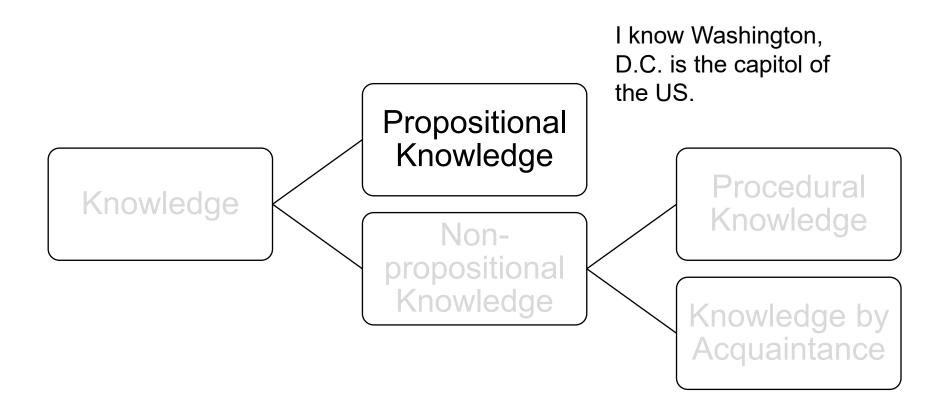


- What is Procedural Knowledge?
- Tasks requiring Procedural knowledge.

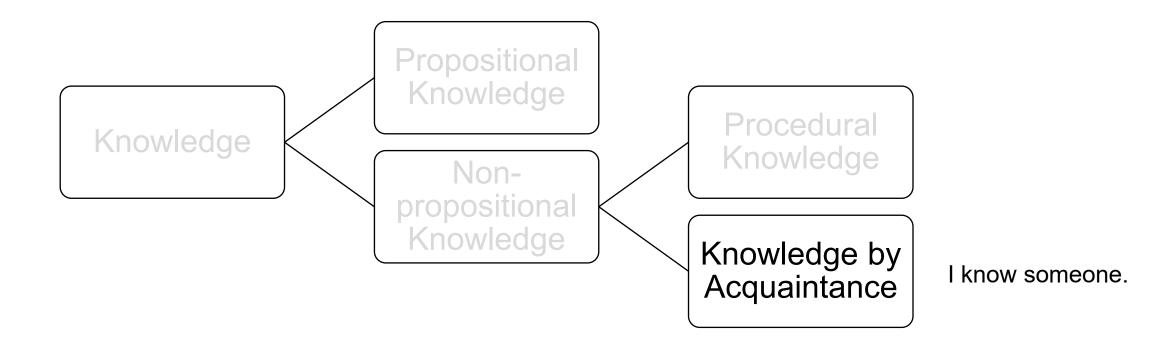




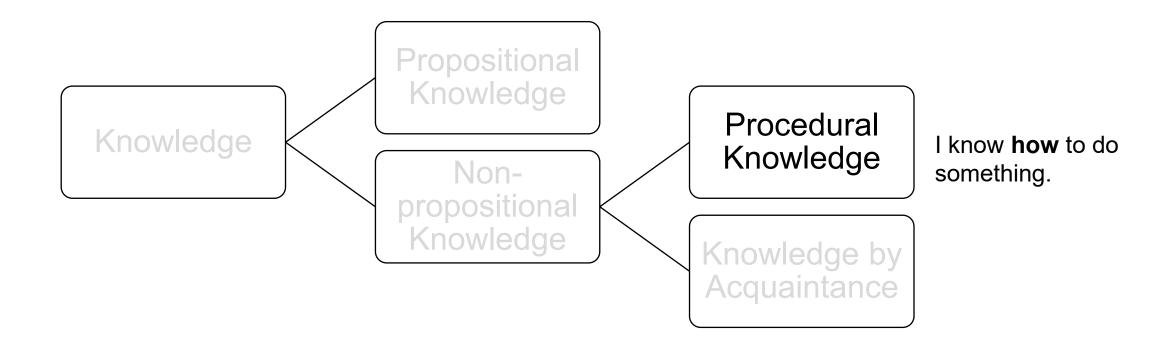






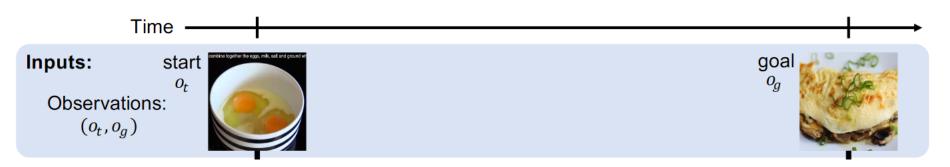








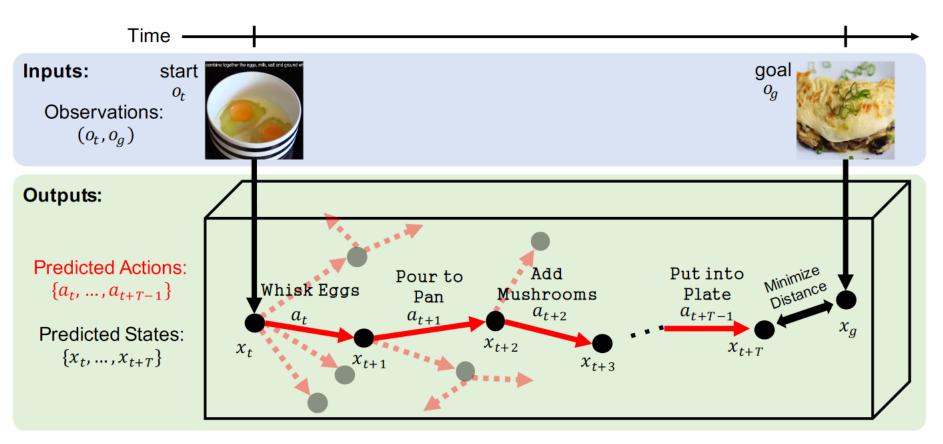
### • Procedural planning



### Given a start image and an end image, generate a sequence of actions.



### • Procedural planning



Given a start image and an end image, generate a sequence of actions.



• Step forecasting



### What is the next step?

Time

Given the historical video, predict the next step.

Frames are from Gordon Ramsay's Fillet of Beef Wellington

Sener, Fadime, and Angela Yao. "Zero-shot anticipation for instructional activities." *Proceedings of the IEEE/CVF International Conference on Computer Vision*. 2019. Lin, Xudong, et al. "Learning to recognize procedural activities with distant supervision." *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2022.



Step forecasting



What is the next step?

Assembling: Shingle the prosciutto on the plastic wrap; Spread mushroom over prosciutto; ...

Given the historical video, predict the next step.

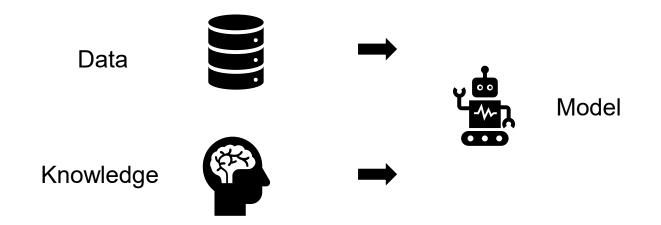
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• Explicit Knowledge Source: Learning with the help of external knowledge



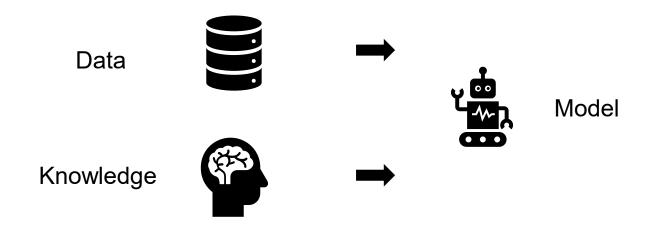
• Implicit Knowledge Source: Learning procedural knowledge from data







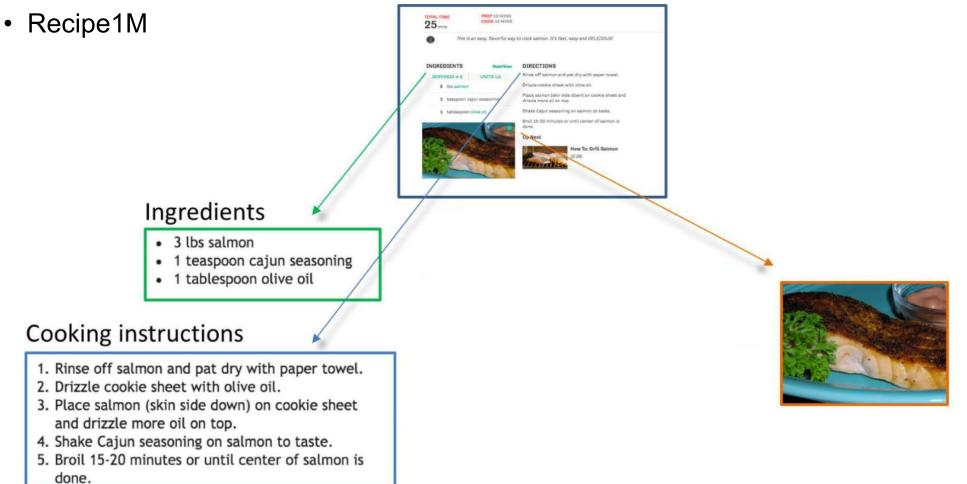
• Explicit Knowledge Source: Learning with the help of external knowledge



### **Explicit Knowledge Source**



• Procedural knowledge can be easily curated from the Internet



### **Explicit Knowledge Source**



- Procedural knowledge can be easily curated from the Internet
  - Recipe1M
  - wikiHow



# Step 1. Sear the filiet mignon to brown.

Over high heat, coat bottom of a heavy skillet with olive oil. Once pan is nearly smoking, sear tenderloin until wellbrowned on all sides.

### Step 2. Fry the mushroom until they

### are dried.

To skillet, add butter and melt over medium heat. Add mushroom mixture and cook until liquid has evaporated.

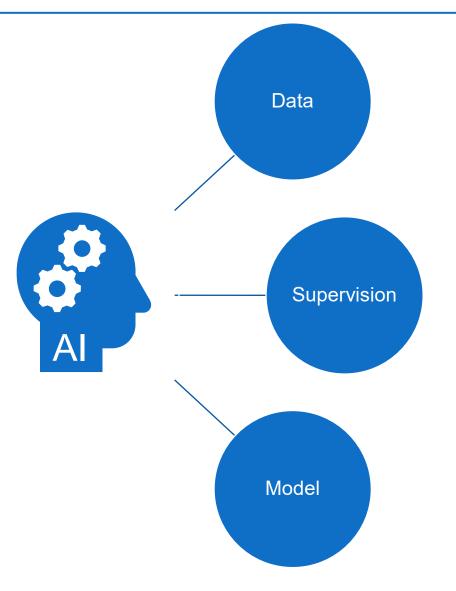
### Step 3. Assembling.

Shingle the prosciutto on the plastic wrap into a rectangle that's big enough to cover the whole tenderloin. Spread the duxelles evenly and thinly over the prosciutto.

••••

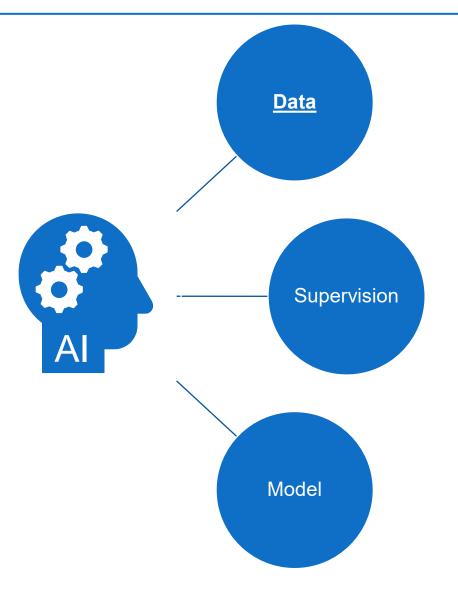
# How to Utilize the Knowledge Source?





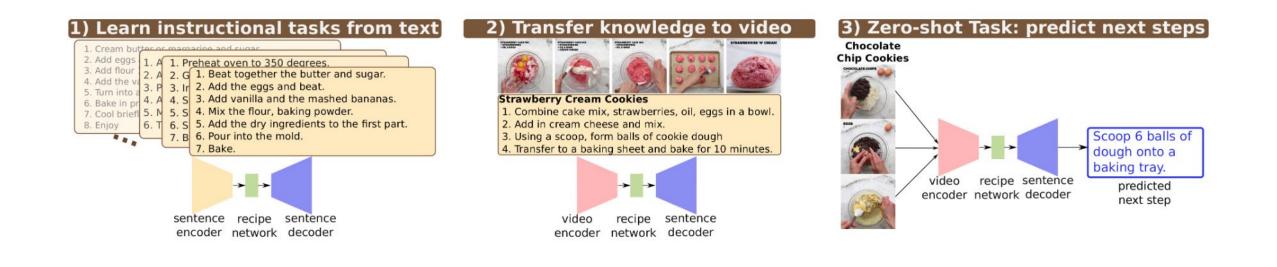
# How to Utilize the Knowledge Source?





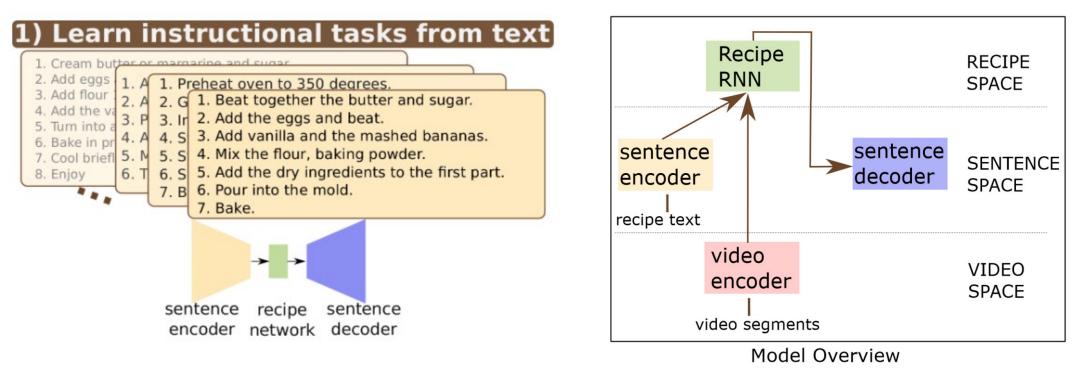


• Key Idea: Obtain training data from knowledge base.



Sener, Fadime, and Angela Yao. "Zero-shot anticipation for instructional activities." *Proceedings of the IEEE/CVF International Conference on Computer Vision*. 2019. Sener, Fadime, Rishabh Saraf, and Angela Yao. "Transferring Knowledge from Text to Video: Zero-Shot Anticipation for Procedural Actions." *IEEE Transactions on Pattern Analysis and Machine Intelligence* 17 (2022).

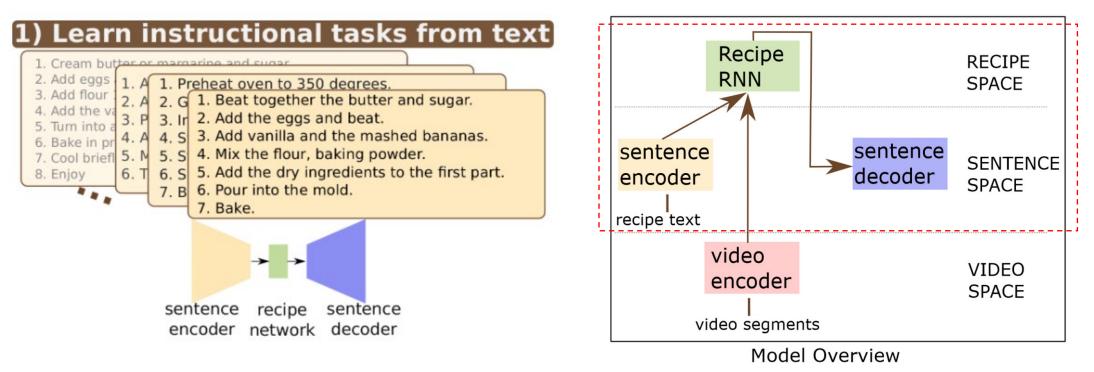
- Sentence encoder encodes a step sentence into a step vector.
- Recipe network is a RNN modeling procedures.
- Sentence decoder decodes step sentences.



Sener, Fadime, and Angela Yao. "Zero-shot anticipation for instructional activities." Proceedings of the IEEE/CVF International Conference on Computer Vision. 2019.

Sener, Fadime, Rishabh Saraf, and Angela Yao. "Transferring Knowledge from Text to Video: Zero-Shot Anticipation for Procedural Actions." *IEEE Transactions on Pattern Analysis and Machine Intelligence* 18 (2022).

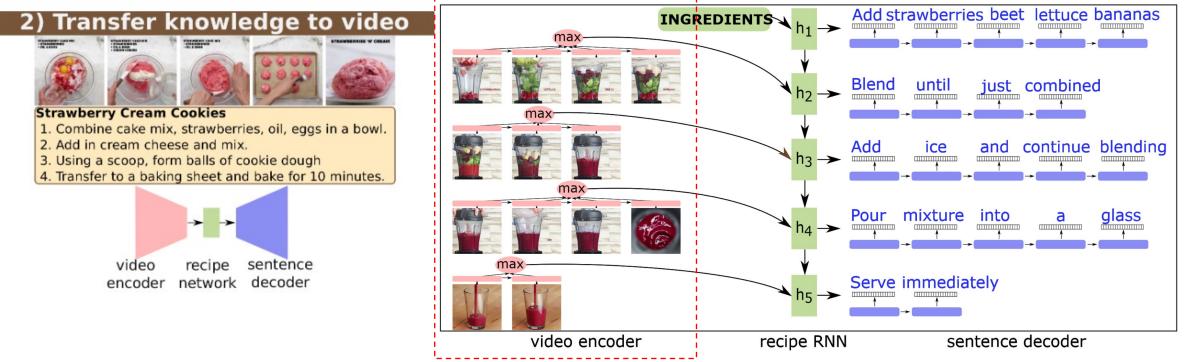
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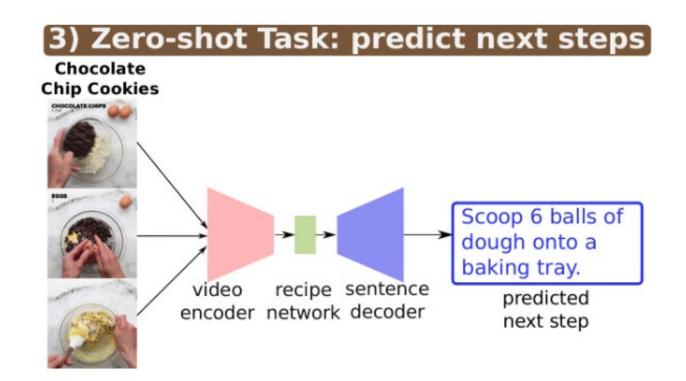
Sener, Fadime, Rishabh Saraf, and Angela Yao. "Transferring Knowledge from Text to Video: Zero-Shot Anticipation for Procedural Actions." *IEEE Transactions on Pattern Analysis and Machine Intelligence* 19 (2022).

• Only train the video encoder to project video into step vectors with annotated data.



Sener, Fadime, and Angela Yao. "Zero-shot anticipation for instructional activities." *Proceedings of the IEEE/CVF International Conference on Computer Vision*. 2019. Sener, Fadime, Rishabh Saraf, and Angela Yao. "Transferring Knowledge from Text to Video: Zero-Shot Anticipation for Procedural Actions." *IEEE Transactions on Pattern Analysis and Machine Intelligence* 20 (2022).

• Generalize on new tasks.



Sener, Fadime, and Angela Yao. "Zero-shot anticipation for instructional activities." *Proceedings of the IEEE/CVF International Conference on Computer Vision*. 2019. Sener, Fadime, Rishabh Saraf, and Angela Yao. "Transferring Knowledge from Text to Video: Zero-Shot Anticipation for Procedural Actions." *IEEE Transactions on Pattern Analysis and Machine Intelligence* 21 (2022).

• Strong zeros-hot performance on the proposed Tasty video dataset

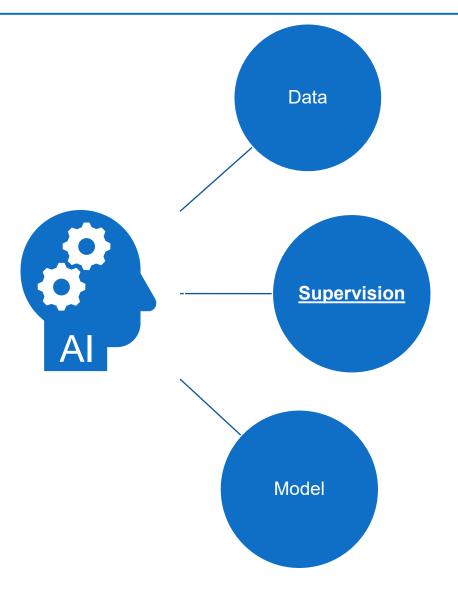
The larger knowledge base used, the better!

Method	ING	VERBS	BLEU1	BLEU4	METEOR
S2VT [53] (GT)	7.59	19.18	18.03	1.10	9.12
S2VT [53], next (GT)	1.54	10.66	9.14	0.26	5.59
End-to-end [60]	-	-	-	0.54	5.48
Ours Visual (GT)	20.40	19.18	19.05	1.48	11.78
Ours Visual	16.66	17.08	17.59	1.23	11.00
Ours Text (100%)	26.09	27.19	26.78	3.30	17.97
Ours Text (50%)	23.01	24.90	25.05	2.42	16.98
Ours Text (25%)	19.43	23.83	23.54	2.03	16.05
Ours Text (0%)	5.80	9.42	10.58	0.24	6.80
Ours Text noING	9.04	22.00	20.11	0.92	13.07
Ours joint video-text	22.27	23.35	21.75	2.33	14.09

- Limitation
  - Domain is limited to cooking.
  - Rely on annotated data samples for training video encoder.

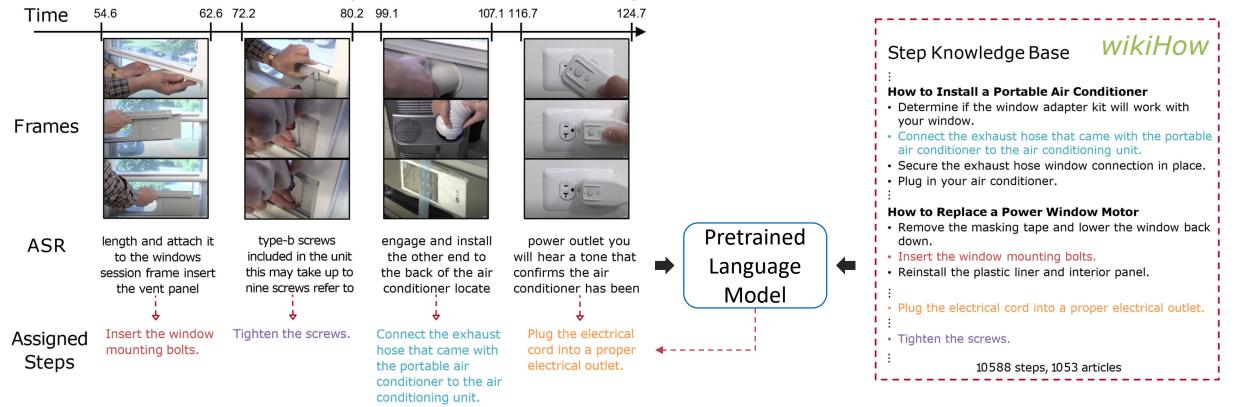
# How to Utilize the Knowledge Source?







• Key Idea: Leverage pretrained language model to align knowledge base and videos with speech to obtain supervision.



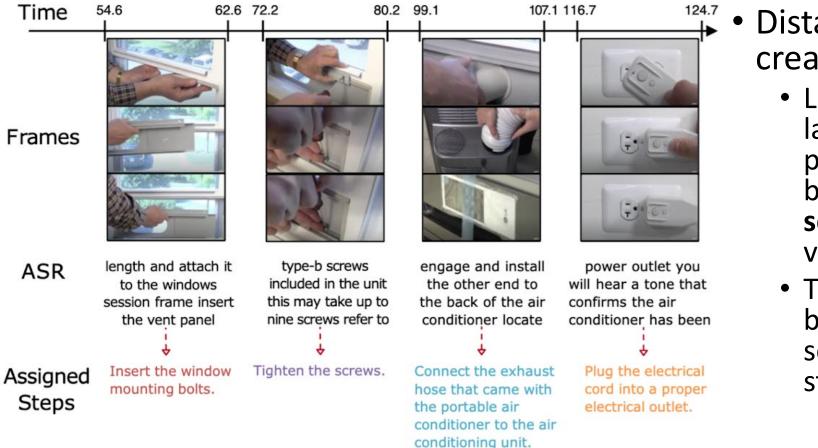
Lin, Xudong, et al. "Learning to recognize procedural activities with distant supervision." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2022.

- Step Knowledge Base Construction
  - Use 1053 tasks, each of which has at least 100 examples in the HowTo100M dataset
  - Find the correspond articles on WikiHow
  - Collect sentences for each step in each of the tasks

Step Knowledge Base <i>WikiHow</i>
<ul> <li>How to Install a Portable Air Conditioner</li> <li>Determine if the window adapter kit will work with your window.</li> <li>Connect the exhaust hose that came with the portable air conditioner to the air conditioning unit.</li> <li>Secure the exhaust hose window connection in place.</li> <li>Plug in your air conditioner.</li> </ul>
<ul> <li>:</li> <li>How to Replace a Power Window Motor</li> <li>Remove the masking tape and lower the window back down.</li> <li>Insert the window mounting bolts.</li> <li>Reinstall the plastic liner and interior panel.</li> </ul>
<ul> <li>Plug the electrical cord into a proper electrical outlet.</li> <li>Tighten the screws.</li> </ul>
: 10588 steps, 1053 articles





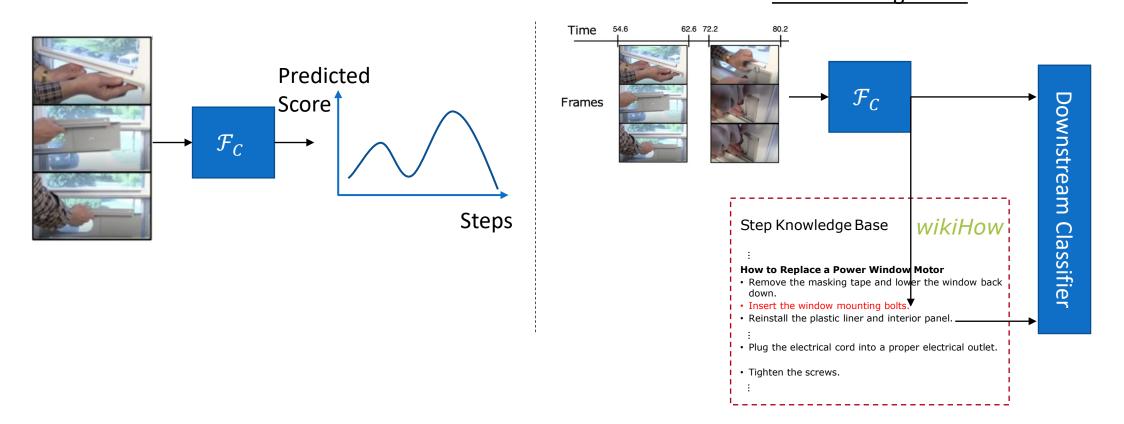


### Distant supervision creation

- Leverage a pretrained language model to produce embeddings for both steps and ASR sentences from the video.
- Then calculate similarity between each ASR sentence and all the steps.



Pretraining: Learning to align videos and the step knowledge base <u>Finetuning: Training a classifier with both step-level</u> <u>video representation and ordering information from</u> the knowledge base





- Step Forecasting on COIN
  - Wikihow Knowledge provides high-quality distant supervision!
  - Ordering information in the knowledge base further helps!

Long-term Model	Segment Model	Pretraining Supervision	Pretraining Dataset	Acc (%)
Basic Transformer	S3D [39]	Unsupervised: MIL-NCE on ASR	HT100M	28.1
Basic Transformer	SlowFast [17]	Supervised: action labels	Kinetics	25.6
Basic Transformer	TimeSformer [8]	Supervised: action labels	Kinetics	34.7
Basic Transformer	TimeSformer [8]	Unsupervised: k-means on ASR	HT100M	34.0
Basic Transformer	TimeSformer	Unsupervised: distant supervision (ours)	HT100M	38.2
Transformer w/ KB Transfer	TimeSformer	Unsupervised: distant supervision (ours)	HT100M	39.4

• The supervision from the wikihow knowledge base also helps

### Recognition of procedural activities on COIN

Long-term Model	Segment Model	Pretraining Supervision	Pretraining Dataset	Acc (%)
TSN (RGB+Flow) [57]	Inception [54]	Supervised: action labels	Kinetics	73.4*
Basic Transformer	S3D [39]	Unsupervised: MIL-NCE on ASR	HT100M	70.2*
<b>Basic Transformer</b>	TimeSformer	Unsupervised: distant supervision (ours)	HT100M	88.9
Transformer w/ KB Transfer	TimeSformer	Unsupervised: distant supervision (ours)	HT100M	90.0

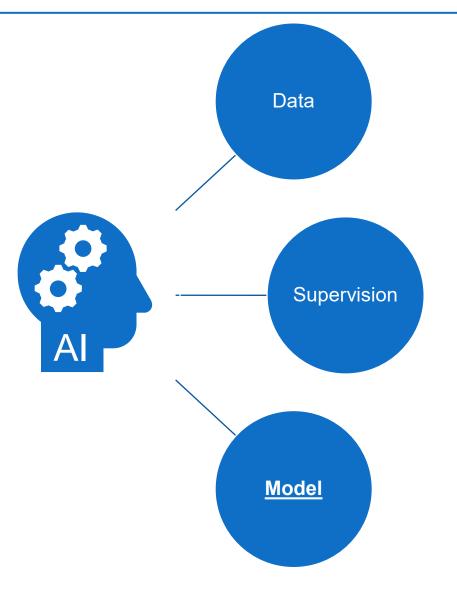
### Egocentric video classification

Segment Model	Pretraining Supervision	Pretraining Dataset	Action (%)	Verb (%)	Noun (%)
ViViT-L [6]	Supervised: action labels	Kinetics	44.0	66.4	56.8
TimeSformer [8]	Supervised: action labels	Kinetics	42.3	66.6	54.4
TimeSformer	Unsupervised: distant supervision (ours)	HT100M	44.4	67.1	58.1

• Limitation: Didn't employ ordering information in the pretraining model.

# How to Utilize the Knowledge Source?



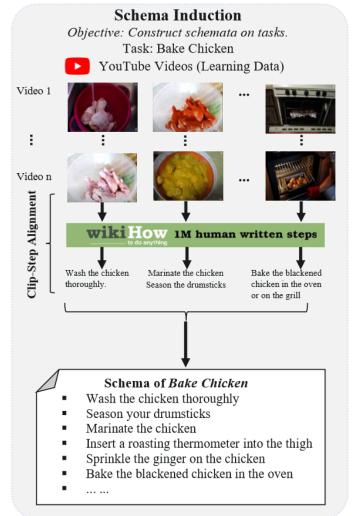


- Induce, Edit, Retrieve: Language Grounded <u>Multimodal Schema for Instructional Video Retrieval</u>
- Key Idea: Learning multimodal schema to represent procedural knowledge.

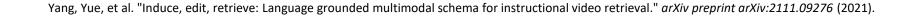


Yang, Yue, et al. "Induce, edit, retrieve: Language grounded multimodal schema for instructional video retrieval." arXiv preprint arXiv:2111.09276 (2021).

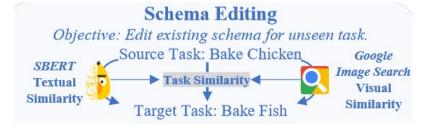
- Schema Induction
  - For each task, find corresponding steps from wikiHow and videos from YouTube.
  - For each segment in each video, retrieve most relevant steps with existing video-text matching models.



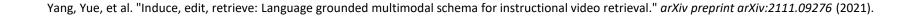




- Schema Editing
  - For an unseen task, find the most similar seen task based on both textual and visual similarity.







- Schema Editing
  - For an unseen task, find the most similar seen task based on both textual and visual similarity
  - Replace object towards the unseen task.





# Multimodal Schema for Instructional Video Retrieval

 For an unseen task, find the most similar seen task based on both textual and visual similarity

Induce, Edit, Retrieve: Language Grounded

Replace object towards the unseen task.

Schema Editing

• Delete steps that are not relevant in the new task with a pretrained language model.

### **Step Deletion**

Source Step 1: Insert a roasting thermometer into the thigh P(Source Step 1 | Bake Fish) << P(Source Step 1 | Bake Chicken) Delete this step.

Source Step 2: Bake the blackened chicken/fish in the oven P(Source Step 2 | Bake Fish)  $\approx$  P(Source Step 2 | Bake Chicken) Include this step.



### • Schema Editing

- For an unseen task, find the most similar seen task based on both textual and visual similarity
- Replace object towards the unseen task.
- Delete steps that are not relevant in the new task with a pretrained language model.
- Replace tokens least likely associated with the task in each step by prompting a pretrained language model.

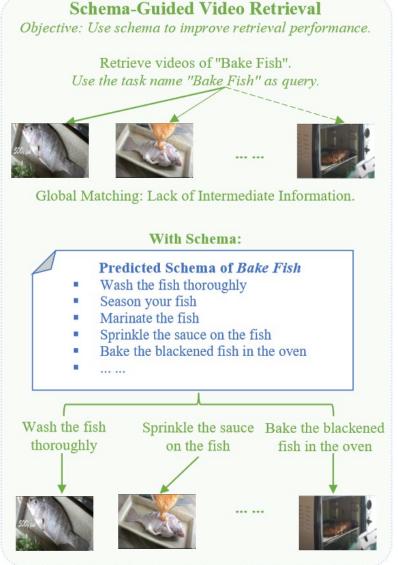
# Token Replacement Source Step: Sprinkle the ginger on the fish Mask the token: Sprinkle the <mask> on the fish Use LM predict a new token: Target Step: Sprinkle the sauce on the fish Predicted Schema of Bake Fish Wash the fish thoroughly Season your fish Marinate the fish Sprinkle the sauce on the fish Bake the blackened fish in the oven .....





#### Even comparable with oracle (using manual step annotation for each query)

- Limitation
  - Schema is restricted to step sequence without considering graph structures, e.g., optional/exchangeable steps.
  - Only evaluated on text-video retrieval.





 The learned schema provides step-level information to better retrieve videos.

	Method	Howto-GEN			COIN			Youcook2								
	Methou	P@1↑	R@5↑	R@10↑	Med r↓	<b>MRR</b> ↑	P@1↑	R@5↑	R@10↑	Med r↓	<b>MRR</b> ↑	P@1↑	R@5↑	R@10↑	Med r↓	<b>MRR</b> ↑
	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
egation	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
ggr	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
βĄ	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
tep	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
Ś	IER <sup>3</sup> (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

# Summary of Methods Using Explicit Knowledge

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Knowledge as data	3) zero-shot Task: predict next steps Grading	Steps were under the server.	<ul> <li>1 A contract of the state of th</li></ul>
Knowledge as data	v		
Knowledge as supervision		$\checkmark$	
Knowledge for model		$\checkmark$	$\checkmark$
Sequential knowledge	$\checkmark$	$\checkmark$	$\checkmark$
Multimodal knowledge			$\checkmark$

# Summary of Methods Using Explicit Knowledge



	Sener & Yao ICCV 2019	Lin et al. CVPR 2022	Yang et al.
Knowledge as data	$\checkmark$		
Knowledge as supervision		$\checkmark$	
Knowledge for model		$\checkmark$	$\checkmark$
Sequential knowledge	$\checkmark$	$\checkmark$	$\checkmark$
Multimodal knowledge			$\checkmark$

• What is next?

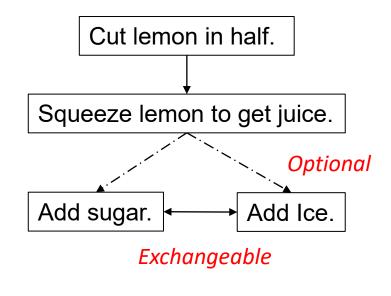
Future Challenge: Is sequential knowledge enough?

- Procedural knowledge:
  - From a sequence to a graph!

#### How to make lemonade?

- 1. Cut lemon in half.
- 2. Squeeze lemon to get juice.
- 3. Add sugar.
- 4. Add Ice.

#### **Current Knowledge**

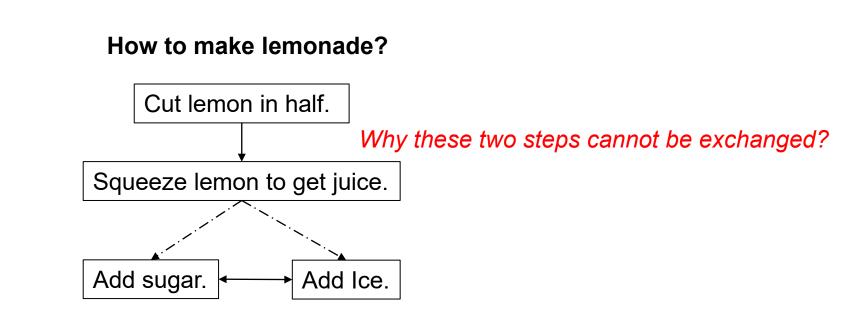


#### Reality

## Future Challenge: Interpret but Not Memorize



• Do models understand **why** the steps are ordered as in the knowledge base?



What is the intent of this step?

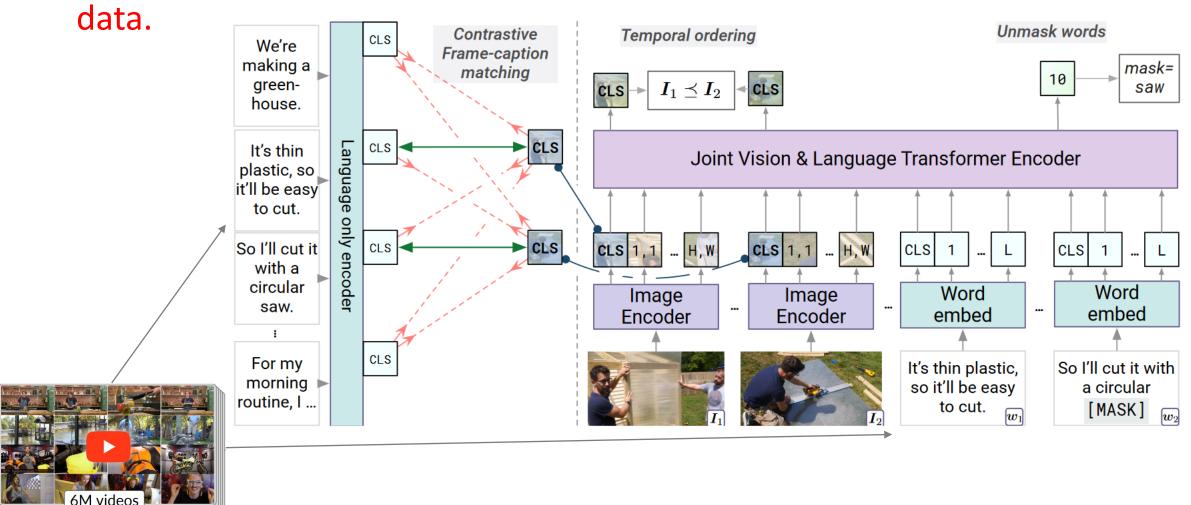




- Explicit Knowledge Source: Learning with the help of external knowledge
- Implicit Knowledge Source: Learning procedural knowledge from data



- Key Idea: Learning temporal reasoning ability through massive video



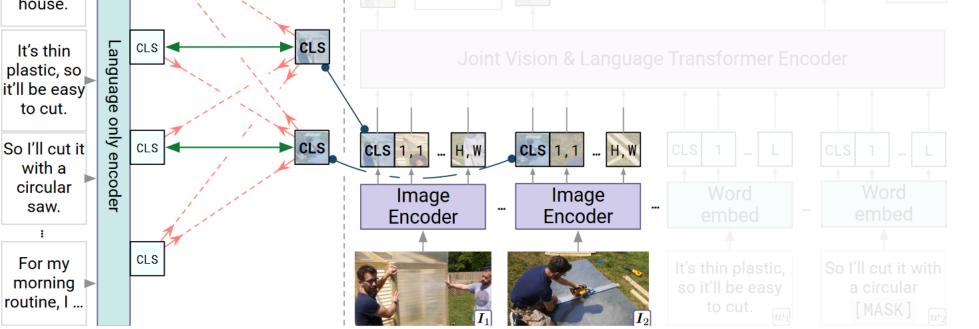
CLS

Contrastive

representations

We're

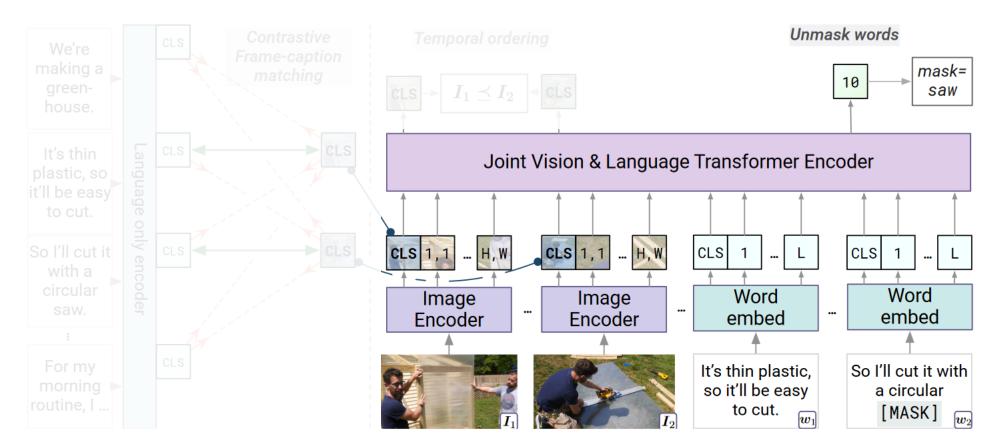






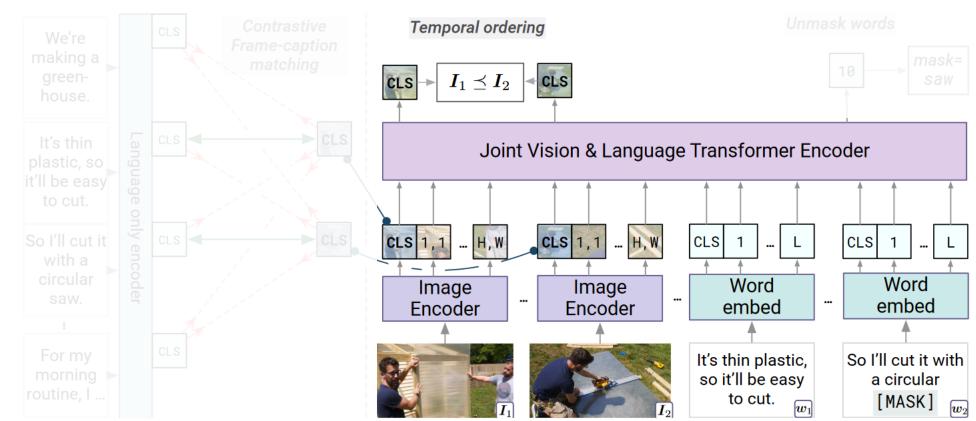


• Objective 2: Masked Token Modeling.





Objective 3: Temporal Ordering (Binary classification between each pair of frames).



### MERLOT: Multimodal Neural Script Knowledge Models



 The model learns strong temporal reasoning ability and joint video-language reasoning ability.

Ordering Images from Visual Stories

	Spearman (↑)	Pairwise acc (†)	Distance $(\downarrow)$
CLIP [89]	.609	78.7	.638
UNITER [22]	.545	75.2	.745
MERIOT	.733	84.5	.498

State-of-the-art over various video-language tasks

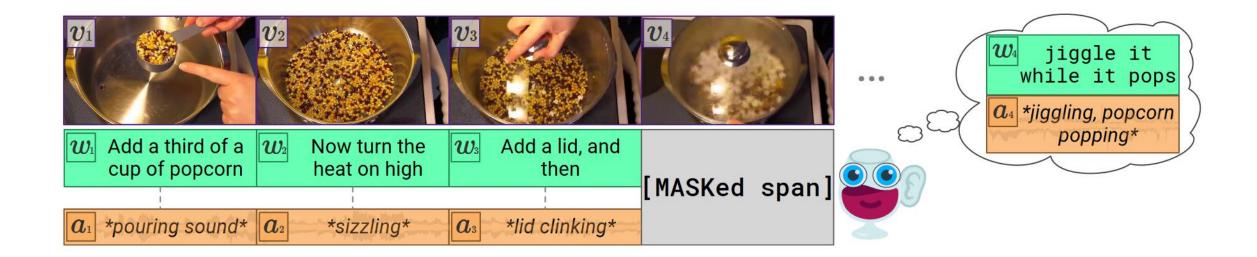
Tasks	Split	Vid. Length	<b>ActBERT</b> [127]	ClipBERT <sub>8x2</sub> [67]	SOTA	MERIOT
MSRVTT-QA	Test	Short	-	37.4	41.5 [118]	43.1
MSR-VTT-MC	Test	Short	88.2	-	88.2 [127]	90.9
TGIF-Action	Test	Short	-	82.8	82.8 [67]	94.0
<b>TGIF-Transition</b>	Test	Short	-	87.8	87.8 [67]	96.2
TGIF-Frame QA	Test	Short	-	60.3	60.3 [67]	69.5
LSMDC-FiB QA	Test	Short	48.6	-	48.6 [127]	52.9
LSMDC-MC	Test	Short	-	-	73.5 [121]	81.7
ActivityNetQA	Test	Long	-	-	38.9 [118]	41.4
Drama-QA	Val	Long	-	-	81.0 [56]	81.4
TVQA	Test	Long	-	-	76.2 [56]	78.7
TVQA+	Test	Long	-	-	76.2 56	80.9
VLEP	Test	Long	-	-	67.5 [66]	68.4

Predict future event given historical videos

• Limitation: short temporal span; importance of the temporal ordering loss is unclear.

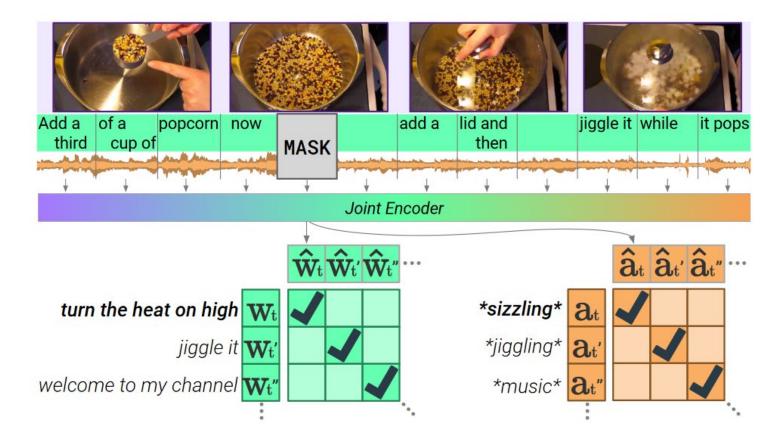
# MERLOT Reserve: Neural Script Knowledge through

• Key Idea: Jointly learn script knowledge with video, language and <u>audio</u>.



# MERLOT Reserve: Neural Script Knowledge through

 Key objective design: <u>contrastive loss</u> between predicted and actual representation of the masked audio/text



# MERLOT Reserve: Neural Script Knowledge through

- Audio brings extra supervision and information towards stronger video understanding and video-language performance.
- Limitation: improvement on learned procedural knowledge may be less significant.

Action Recognition

Model

Only

/ision

Audio

VATT-Base<sup>[2]</sup>

VATT-Large [2]

Florence [125]

MTV-Base [122]

MTV-Large [122]

MTV-Huge [122]

RESERVE-B

**RESERVE-L** 

**RESERVE-B** 

**PRESERVE-L** 

TimeSFormer-L [9]

Kinetics-600 (%)

Top-1 Top-5

95.5

96.6

95.6

97.8

96.1

96.7

98.3

95.8

96.3

80.5

83.6

82.2

87.8

83.6

85.4

89.6

88.1

89.4

89.7 96.6

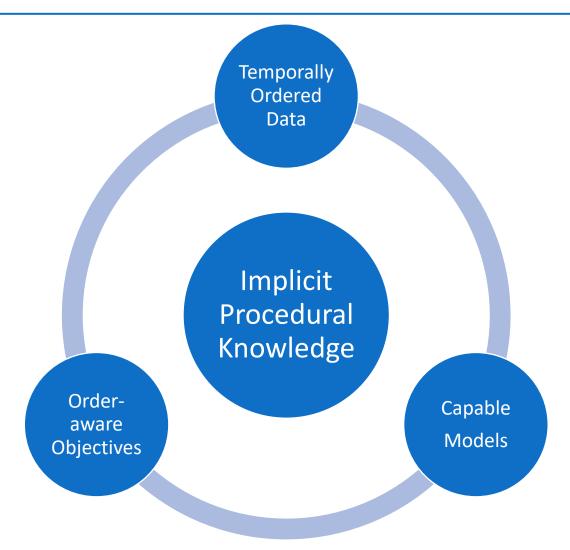
91.1 97.1

	Model	Interaction	( Sequence	test acc; % Prediction		Overall
_	Supervised SoTA	39.8	43.6	ClipBER 32.3	T [74] 31.4	36.7
zero-shot	Random CLIP (VIT-B/16) [92] CLIP (RN50x16) [92] Just Ask (ZS)[123]	25.0 39.8 39.9	25.0 40.5 41.7	25.0 35.5 36.5	25.0 36.0 <b>37.0</b>	25.0 38.0 38.7
Z	<ul> <li>RESERVE-B</li> <li>RESERVE-L</li> <li>RESERVE-B (+audio)</li> <li>RESERVE-L (+audio)</li> </ul>	44.4 42.6 <b>44.8</b> 43.9	40.1 41.1 <b>42.4</b> 42.6	38.1 37.4 <b>38.8</b> 37.6	35.0 32.2 36.2 33.6	39.4 38.3 <b>40.5</b> 39.4

Situated Reasoning (STAR)

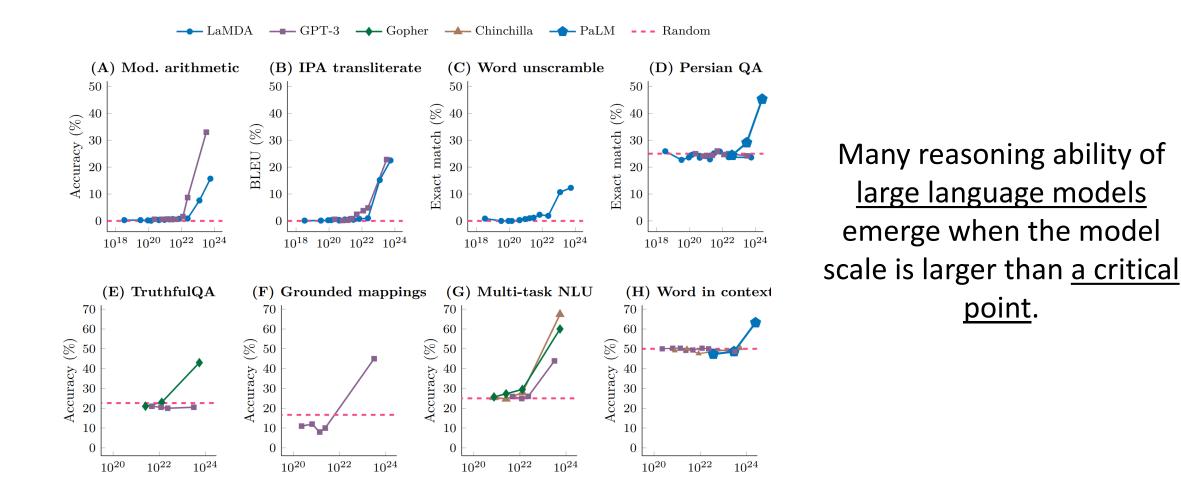
### Summary of Methods Learning Implicit Knowledge





### Future Challenge: Is there a critical point on scale?

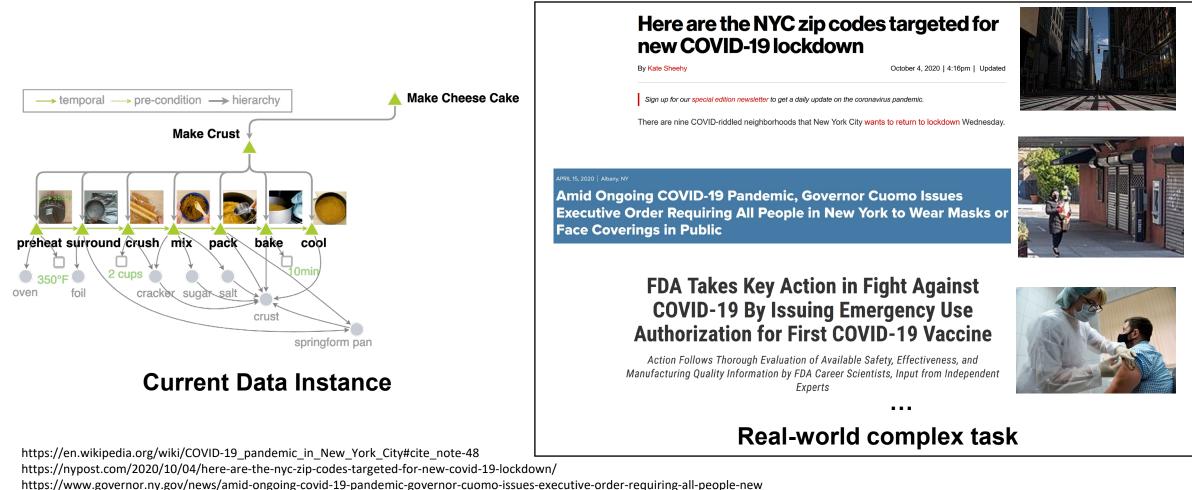
- Can models learn procedural knowledge with a limited scale?



Wei, Jason, et al. "Emergent abilities of large language models." arXiv preprint arXiv:2206.07682 (2022).

## Future Challenge: From an instance to a set

• Can models learn from temporally ordered sets of instances?



https://www.fda.gov/news-events/press-announcements/fda-takes-key-action-fight-against-covid-19-issuing-emergency-use-authorization-first-covid-19-issuing-em

https://www.nature.com/articles/d41586-020-02684-9

### **Take-away Messages**



