

Action	Template
[Find] <Object>	Find Object
[Walk] <Object>	Walk to Object
[Run] <Object>	Run to Object
[Sit] <Object>	Sit on Object
[StandUp]	Stand up
[Grab] <Object>	Grab Object
[Open] <Object>	Open Object
[Close] <Object>	Close Object
[Put] <Object_1> <Object_2>	Put Object_1 on Object_2
[PutIn] <Object_1> <Object_2>	Put Object_1 in Object_2
[SwitchOn] <Object>	Switch/Turn on Object
[SwitchOff] <Object>	Switch/Turn off Object
[Drink] <Object>	Drink Object
[TurnTo] <Object>	Turn to Object
[LookAt] <Object>	Look at Object
[Wipe] <Object>	Wipe Object
[PutOn] <Object>	Put on Object
[PutOff] <Object>	Put off Object
[Greet] <Object>	Greet Object
[Drop] <Object>	Drop Object
[Touch] <Object>	Touch Object
[Lie] <Object>	Lie on Object
[Pour] <Object_1> <Object_2>	Pour Object_1 into Object_2
[Type] <Object>	Type Object
[Watch] <Object>	Watch Object
[Move] <Object>	Move Object
[Wash] <Object>	Wash Object
[Rinse] <Object>	Rinse Object
[Scrub] <Object>	Scrub Object
[Squeeze] <Object>	Squeeze Object
[PlugIn] <Object>	Plug in Object
[PlugOut] <Object>	Plug out Object
[Cut] <Object>	Cut Object
[Eat] <Object>	Eat Object
[Sleep]	Sleep
[WakeUp]	Wake up

Table 4: Supported actions in VirtualHome and their corresponding text templates.

## A Appendix

### A.1 VirtualHome

The complete format of an executable action step in VirtualHome is `<char{char_id}> [Action] <Object> (Object_id)`. Specifically, `char_id` specifies which agent to execute the action when multiple agents are in the world model at the same time. Action should be a supported atomic action in VirtualHome. Object is the object with which the agent interacts. Each object in the environment is assigned an `Object_id` to distinguish it from others of the same object class. We designed a template for each action to transform them into natural text for LMs finetuning. The full list of executable actions can be found in Table 4. Note that in the list, we omit `<char{char_id}>` and `(Object_id)` for simplicity.

### A.2 Activity Goal And Predicate

The goal of an household activity in VirtualHome consists of several predicates. Each predicate represents a condition of one object or a relation between two objects. For example, `OPEN(coffee`

567 maker) means the coffee maker is open, and ON(apple, table) means an apple is on the table.  
568 The goal is only achieved when all the predicates are achieved. We collected activities and goals from  
569 RobotHow.

### 570 A.3 Data Format and Prompts

571 Following Chung et al. [8], we use instructions with in-context exemplars as prompts. Specifically,  
572 the instruction, the question context, and the answer will be provided in each exemplar, and the full  
573 prompt will contain multiple such exemplars for in-context learning. The format of the data and the  
574 exemplar for each task is provided below.

#### 575 A.3.1 Plan Generation

##### 576 Data Example

577

Key	Value
activity	watch TV
condition	living room, sofa, TV. The sofa and TV are in the living room.
plan	Walk to living room. Sit on sofa. Watch TV.

##### 578 In-context Exemplar

579

Q: How to {{ activity }}? Given items include {{ condition }}  
A: {{ plan }}

#### 580 A.3.2 Housework QA

##### 581 Data Example

582

Key	Value
activity	watch TV
choices	[TV, coffee, bed, toothbrush]
answer	TV

##### 583 In-context Exemplar

584

Question: To {{ activity }}, a possibly related item could be  
Answer: {{ answer }}

#### 585 A.3.3 Negation Housework QA

##### 586 Data Example

587

Key	Value
activity	watch TV
choices	[TV, sofa, living room, toothbrush]
answer	toothbrush

##### 588 In-context Exemplar

589

Question: To {{ activity }}, an unrelated item could be  
Answer: {{ answer }}

#### 590 A.3.4 Activity Recognition

##### 591 Data Example

592

Key	Value
plan	Walk to living room. Sit on sofa. Watch TV.
choices	[watch TV, make coffee, sleep, brush teeth]
activity	watch TV

##### 593 In-context Exemplar

594

Given a task plan: `{{ plan }}`  
Question: what is the name of this task?  
Answer: `{{ answer }}`

#### 595 A.3.5 Activity Inference

##### 596 Data Example

597

Key	Value
state	Tom is sitting on the sofa. Tom is facing the TV.
choices	[watch TV, make coffee, sleep, brush teeth]
activity	watch TV

##### 598 In-context Exemplar

599

`{{ state }}`  
Question: given the above state, a possible activity could be  
Answer: `{{ answer }}`

#### 600 A.3.6 Counting

##### 601 Data Example

602

Key	Value
movement	Tom was at home. He grabbed an apple and put it on the bookshelf. He then walked to the kitchen and scrub a plate. He went back to bookshelf and put the plate on it.
location	bookshelf
number	2
items	apple, plate

##### 603 In-context Exemplar

604

Given a sequence of actions in a house, and a question about what items are located in a specific place. Answer the number of items and list the items.

Q: `{{ movement }}` How many items are there on the `{{ location }}`?  
A: There are `{{ number }}` items on the `{{ location }}`. They are `{{ items }}`

605 **A.3.7 Counting QA**

606 **Data Example**

607

Key	Value
movement	Tom was at home. He grabbed an apple and put it on the bookshelf. He then walked to the kitchen and scrub a plate. He went back to bookshelf and put the plate on it.
location	bookshelf
number	2

608 **In-context Exemplar**

609

Q: `{{ movement }}` How many items are there on the `{{ location }}`?  
A: `{{ number }}`

610 **A.3.8 Object Path Tracking**

611 **Data Example**

612

Key	Value
movement	Tom went to the kitchen. Mary walked into the dining room. Tom grabbed a plate. Tom travelled to the living room. Mary moved to the living room. Tom put the plate on the table. Mary grabbed the plate. Mary journeyed to the bedroom.
object	plate
path	kitchen, living room, bedroom

613 **In-context Exemplar**

614

`{{ movement }}`  
Question: What is the order of the rooms where the `{{ object }}` appeared?  
Answer: `{{ path }}`

615 **A.3.9 Object Location QA**

616 **Data Example**

617

Key	Value
movement	Tom went to the kitchen. Mary walked into the dining room. Tom grabbed a plate. Tom travelled to the living room. Mary moved to the living room. Tom put the plate on the table. Mary grabbed the plate. Mary journeyed to the bedroom.
object	plate
reference_room	living room
preposition	before
answer	kitchen

618 **In-context Exemplar**

619

`{{ movement }}`  
Question: Where is the `{{ object }}` `{{ preposition }}` the `{{ reference_room }}`?  
Answer: `{{ answer }}`

## A.4 Hyperparameters

For both GPT-Neo-1.3B and GPT-J-6B, we use a learning rate of  $8 \times 10^{-5}$  and a batch size of 20. The weights for plan generation, activity recognition, counting, and object path tracking are 1.0, 0.7, 1.0, and 1.0, respectively. We trained GPT-Neo-1.3B for 3 epochs with the EWC coefficient  $\lambda = 0.5$  in Equation 4. For GPT-J-6B, we trained it for 5 epochs with  $\lambda = 2$ . With our approach, it takes 40 minutes to train a GPT-Neo and 220 minutes to train a GPT-J. We used a rank of 8 and coefficient of 32 for LoRA’s hyperparameters.

## A.5 bAbI Dataset

We include 8 tasks from bAbI that test embodied knowledge. They are: One Supporting Fact, Two Supporting Fact, Three Supporting Fact, Counting, Lists/Sets, Simple Negation, Time Reasoning, Positional Reasoning. Examples for each task are shown in Table 5.

<b>Task 1: Single Supporting Fact</b> Mary went to the bathroom. John moved to the hallway. Mary travelled to the office. Where is Mary? <b>A:office</b>	<b>Task 2: Two Supporting Facts</b> John is in the playground. John picked up the football. Bob went to the kitchen. Where is the football? <b>A:playground</b>
<b>Task 3: Three Supporting Facts</b> John picked up the apple. John went to the office. John went to the kitchen. John dropped the apple. Where was the apple before the kitchen? <b>A:office</b>	<b>Task 4: Counting</b> Daniel picked up the football. Daniel dropped the football. Daniel got the milk. Daniel took the apple. <b>A: office</b> How many objects is Daniel holding? <b>A: two</b>
<b>Task 5: Lists/Sets</b> Daniel picks up the football. Daniel drops the newspaper. Daniel picks up the milk. What is Daniel holding? <b>milk, football</b>	<b>Task 6: Simple Negation</b> Sandra travelled to the office. Fred is no longer in the office. Is Fred in the office? <b>A:no</b> Is Sandra in the office? <b>A:yes</b>
<b>Task 7: Time Reasoning</b> In the afternoon Julie went to the park. Yesterday Julie was at school. Julie went to the cinema this evening. Where did Julie go after the park? <b>A:cinema</b> Where was Julie before the park? <b>A:school</b>	<b>Task 8: Positional Reasoning</b> The triangle is to the right of the blue square. The red square is on top of the blue square. The red sphere is to the right of the blue square. Is the red sphere to the right of the blue square? <b>A:yes</b> Is the red square to the left of the triangle? <b>A:yes</b>

Table 5: Examples for bAbI tasks.

## A.6 Experimental Results

Experimental results on our constructed downstream tasks are shown in Table 6, and the results on bAbI are shown in Table 7. We also show the results of ablation studies in Table 8.

## A.7 Broader Impact

Like other generation systems, the language model trained by our approach is susceptible to producing unintended output when confronted with harmful input, such as unethical text or input intended for adversarial attacks. Therefore, we strongly advise against utilizing our approach outside of controlled research environments until these risks have been mitigated. It is important to note that a thoughtless deployment of our method could potentially enable malicious exploitation of the underlying language models. Thus, precautions, such as implementing a filtering mechanism, must be taken.

Task	Metric	GPT-Neo		GPT-J		ChatGPT (GPT3.5-turbo)
		Base	Ours	Base	Ours	
Plan Generation						
-Vanilla Seen	Rouge-L	21.25	49.70	34.31	<b>51.23</b>	40.57
-Vanilla UnSeen	Rouge-L	17.64	49.27	34.22	<b>49.58</b>	41.01
-Confusing Seen	Rouge-L	16.86	46.88	34.81	<b>48.94</b>	40.41
-Confusing Unseen	Rouge-L	17.05	42.34	32.98	<b>45.60</b>	40.97
Housework QA	Accuracy	70.11	72.41	77.78	<b>85.44</b>	83.91
Negation Housework QA	Accuracy	38.27	<b>41.98</b>	35.19	39.51	87.65
Activity Recognition	Accuracy	69.22	85.43	87.98	<b>88.52</b>	95.05
Activity Inference	Accuracy	56.49	66.03	69.08	<b>74.43</b>	83.59
Counting	Accuracy	22.68	28.87	30.41	<b>67.01</b>	66.49
Object Path Tracking	LCS	30.80	85.91	33.86	<b>98.67</b>	59.53
Object Location QA	Accuracy	22.50	33.50	30.00	<b>34.50</b>	67.50

Table 6: Experimental results on various downstream evaluation tasks. The best result among baselines and our method is shown in **bold**, and the best result among all the models is underlined.

Task	GPT-Neo		GPT-J		ChatGPT
	Base	Ours	Base	Ours	
Single Supporting Fact	51.86	56.29	65.16	<b>68.98</b>	96.27
Two Supporting Fact	33.43	30.82	<b>40.48</b>	26.08	47.33
Three Supporting Fact	7.85	13.49	22.46	<b>30.41</b>	16.82
Counting	34.04	48.84	41.39	<b>69.08</b>	93.96
Lists/Sets	14.80	51.76	34.74	<b>84.99</b>	76.84
Simple Negation	36.05	<b>65.56</b>	42.80	63.95	93.66
Time Reasoning	21.45	23.46	36.96	<b>59.42</b>	61.63
Positional Reasoning	50.51	<b>53.64</b>	49.70	53.23	58.38

Table 7: Experimental results on bAbI test sets.

	Base	Ours	-w/o Plan Gen	GPT-Neo -w/o Act Recog	-w/o Count	-w/o Obj PT
Plan Gen						
-Vanilla / Seen	21.25	49.70	14.48	49.38	49.85	<b>50.06</b>
-Vanilla / Unseen	17.64	49.27	14.28	48.96	<b>51.16</b>	49.02
-Confusing / Seen	16.86	46.88	13.63	46.37	48.30	<b>49.14</b>
-Confusing / Unseen	17.05	42.34	9.86	43.79	<b>46.28</b>	44.64
QA	70.11	72.41	73.18	71.26	<b>74.71</b>	70.11
Neg QA	38.27	<b>41.98</b>	32.72	35.80	36.42	38.89
Act Recog	69.22	85.43	<b>85.97</b>	48.63	85.25	84.34
Act Infer	56.49	<b>66.03</b>	<b>66.03</b>	58.40	64.89	62.21
Count	22.68	28.87	18.56	25.26	<b>35.05</b>	32.99
Obj PT	30.80	85.91	<b>92.13</b>	84.17	86.46	29.90
Obj QA	22.50	33.50	35.00	<b>49.00</b>	43.50	22.00
Perplexity	4.120*	4.193	4.171	<b>4.151</b>	4.162	4.164

Table 8: Ablation experimental results on training tasks.