EgoTV : Egocentric Task Verification from Natural Language Task Descriptions

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Abstract

To enable progress towards egocentric agents capable of understanding everyday tasks specified in natural language, we propose a benchmark and a synthetic dataset called Egocentric Task Verification (EgoTV). The goal in EgoTV is to verify the execution of tasks from egocentric videos based on the natural language description of these tasks. EgoTV contains pairs of videos and their task descriptions for multi-step tasks – these tasks contain multiple sub-task decompositions, state changes, object interactions, and sub-task ordering constraints. In addition, EgoTV also provides abstracted task descriptions that contain only partial details about ways to accomplish a task. Consequently, EgoTV requires causal, temporal, and compositional reasoning of video and language modalities, which is missing in existing datasets. We also find that existing vision-language models struggle at such all round reasoning needed for task verification in EgoTV. Inspired by the needs of EgoTV, we propose a novel Neuro-Symbolic Grounding (NSG) approach that leverages symbolic representations to capture the compositional and temporal structure of tasks. We demonstrate NSG's capability towards task tracking and verification on our EgoTV dataset and a real-world dataset derived from CrossTask [82] (CTV). We open-source the EgoTV and CTV datasets and the NSG model for future research on egocentric assistive agents.

1. Introduction

Inspired by recent progress in visual systems [40, 65], we consider an assistive egocentric agent capable of reasoning about daily activities. When invoked via natural language commands, for e.g., while baking a cake, the agent understands the steps involved in baking, tracks progress through the various stages of the task, detects and proactively prevents mistakes by making suggestions. Such a virtual agent [11] would empower users to learn new skills and accomplish tasks efficiently.

Developing this egocentric agent capable of tracking and verifying everyday tasks based on their natural language specification is challenging for multiple reasons. First, such an agent must reason about various ways of doing a *multi-step* task specified in natural language. This entails decomposing the task into relevant actions, state changes, object interactions as well as any necessary causal and temporal relationships between these entities. Secondly, the agent must ground these entities in egocentric observations to track progress and detect mistakes. Lastly, to truly be useful, such an agent must support tracking and verification for a combination of tasks and, ideally, even unseen tasks. These three challenges – causal and temporal reasoning about task structure from natural language, visual grounding of sub-tasks, and compositional generalization – form the core goals of our work.

As our first contribution, we propose a benchmark – ***Ego****centric* ***T****ask* ***V****erification* (EgoTV) – and a corresponding dataset in the AI2-THOR [29] simulator. Given a natural language (NL) task description and a corresponding egocentric video of an agent, the goal of EgoTV is to verify whether the task was successfully completed in the video or not. EgoTV contains multi-step tasks with *ordering* constraints on the steps and *abstracted* NL task descriptions with omitted low-level task details inspired by the needs of real-world assistants. We also provide splits of the dataset focused on different generalization aspects, e.g., unseen visual contexts, compositions of steps, and tasks (see Figure 1). Consequently, EgoTV dataset provides the fine-grained control necessary for rigorous testing and refinement of task reasoning models, which is often missing in real-world datasets [17, 10]. Yet, EgoTV mirrors the real world by leveraging visual photo-realism and task diversity.

Our second contribution is a novel approach for order-aware visual grounding – ***Neuro****-****S****ymbolic* ***G****rounding* (NSG), capable of compositional reasoning and generalizing to unseen tasks owing to its ability to leverage ab-

*Work done while interning at Meta.

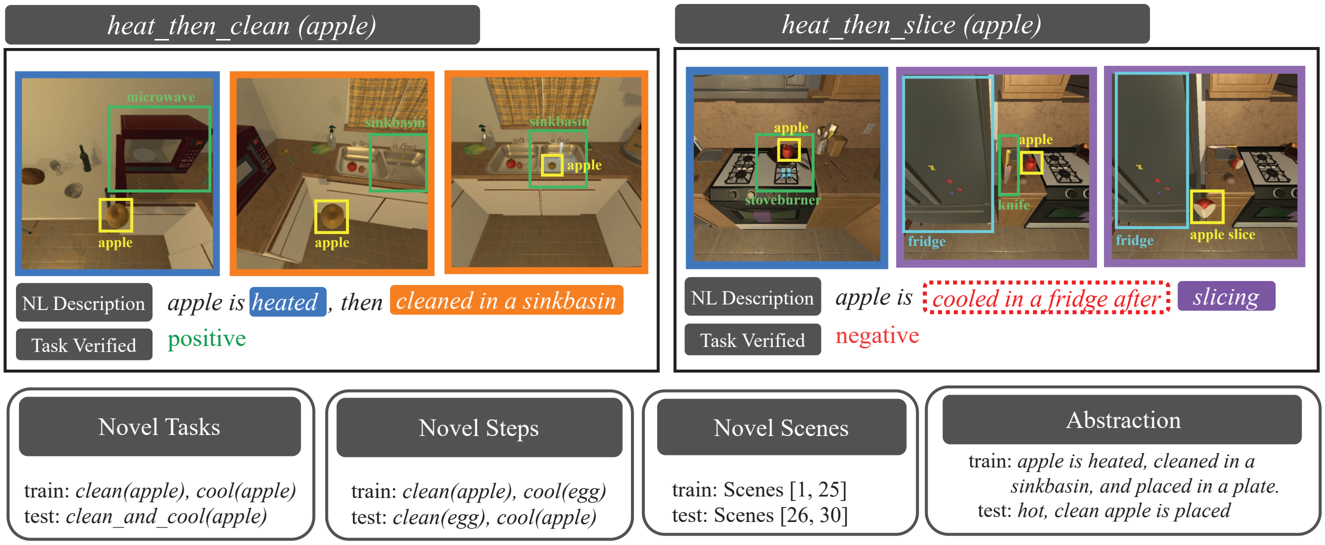


Figure 1. **EgoTV benchmark.** A positive example [Left] and a negative example [Right] from the train set along with illustrative examples from the test splits [Bottom] of EgoTV are shown. The test splits are focused on generalization to novel compositions of tasks, unseen sub-tasks or steps and scenes, and abstraction in NL task descriptions. The bounding boxes are solely for demonstration purposes and are not used during training/inference.

stract NL descriptions along with compositional and temporal structure of tasks (task decomposition, ordering). In contrast, state-of-the-art vision-language models [76, 50, 36, 3] struggle to ground NL descriptions in egocentric videos, and do not generalize to unseen tasks. NSG outperforms these models by $\mathbf{33.8}\%$ on compositional generalization and $\mathbf{32.8}\%$ on abstractly described task verification. Finally, to evaluate NSG on real-world data, we instantiate EgoTV on the CrossTask [82] instructional video dataset. We find that it also outperforms state-of-the-art models at task verification on CrossTask. We hope that the EgoTV benchmark and dataset will enable future research on egocentric agents capable of aiding in everyday tasks.

2. Related Work

Video-based Task Understanding. Understanding tasks from videos has been a long-standing theme in vision research with focus on recognizing activities [58, 10], human-object interactions [25, 17], and object state changes [60, 14] using egocentric or exocentric videos. But apart from recognizing actions, objects, and state changes, task verification also requires understanding temporal orderings between them. Our work is, therefore, closer to research on understanding instructional tasks [82, 62], which require reasoning about multiple, ordered steps. Prior works focus on either learning the order of steps [4, 37, 24, 42] or use step-ordering as a supervisory signal for learning step-representations or step-segmentation [82, 56]. Instead, we are focused on video-based order verification of steps described in NL, akin to [49].

Temporal Video Grounding. Our EgoTV benchmark is also closely related to the problem of Temporal Video Grounding (TVG) [43, 20, 52, 60]. However, prior work on TVG predominantly focuses on localizing a single action in the video [59, 27]. In contrast, EgoTV requires localizing multiple actions, wherein actions could have partial ordering, i.e., actions could have more than one valid ordering amongst them.

Vision-Language Benchmarks. Various benchmark tasks have been proposed for enabling models that can reason across video and language modalities (see Table 1). Examples include video question answering [74, 69, 18, 21, 68, 31, 63, 16], video-based entailment [38], and embodied task completion [57, 47, 61]. However, these benchmarks focus on individual specific aspects of multimodal reasoning, e.g., compositional reasoning (AGQA [18], ActivityNet-QA [21], TVQA [31], and CATER [16]) or causal reasoning (NExT-QA [69], CoPhy [5], Causal-VidQA [33], EgoTaskQA[26], and VIOLIN [38]). In comparison, EgoTV focuses on both causal and compositional reasoning and further requires visual grounding of both objects and actions from text, similar to STAR [68] and CLEVRER [74], albeit in egocentric settings. Unlike embodied task completion benchmarks whose objective is to develop robotic agents that can *perform everyday tasks* through task-planning (ALFRED [57], TEACh [47]) and control (Behavior [61]), EgoTV benchmark's objective is to develop virtual agents that can *track and verify everyday tasks* performed by humans. Akin to NLP *Entailment* problem [9, 70], it can also be viewed as a video-based entailment problem – where a given "premise" (video) is val-

	Reasoning			Dataset Characteristics		
	compositional	causal	temporal	egocentric	real-world	diagnostic tools
CLEVRER [74]	✓	✓	✓	✗	✗	✓
Next-QA [69]	✗	✓	✓	✗	✓	✓
ActivityNet-QA [21]	✗	✗	✓	✗	✓	✗
STAR [68]	✓	✓	✓	✗	✓	✓
Causal-VidQA [33]	✗	✓	✗	✗	✓	✓
EPIC-KITCHENS [10]	✓	✓	✗	✓	✓	✓
Ego-4D [17]	✗	✓	✗	✓	✓	✓
VIOLIN [38]	✗	✓	✗	✗	✓	✗
Cross-Task [82]	✓	✓	✓	✗	✓	✗
EgoTV	✓	✓	✓	✓	✗	✓

Table 1. **EgoTV vs. existing video-language datasets.** EgoTV benchmark enables systematic investigation (diagnostics) on compositional, causal (e.g., effect of actions), and temporal (e.g., action ordering) reasoning in egocentric settings. Table 5 in Appendix provides a more comprehensive comparison.

idated by a "hypothesis" (task description).

Vision-Language Models. Vision-Language Models (VLMs) [50, 36, 39, 32, 76] pre-trained on large-scale image-text or video-language narration pairs have demonstrated enhanced performance on certain compositional [34] and causal [60] tasks. However, they generally struggle to handle compositionality and order sensitivity [77, 64]. Instead, NSG explicitly targets order awareness and compositionality for generalization in task verification using neuro-symbolic reasoning.

Neuro-symbolic Models. Neuro-symbolic models combine feature extraction through deep learning with symbolic reasoning [54, 68] to capture compositional substructures. These models either reason on static images to recognize object attributes and relations (NS-CL [41], NS-VQA [75], CLOSURE [6], and $\nabla-$FOL [2]), or on videos to recognize spatio-temporal and causal relations (NS-DR [74] and DCL [8]). We extend this to tracking multi-step actions.

3. EgoTV Benchmark and Dataset

We present the ***Ego**centric **T**ask **V**erification* (EgoTV) benchmark and dataset. To enable task tracking and verification for egocentric agents, EgoTV contains: 1) *multi-step* tasks with *ordering constraints* to capture the causal and temporal nature of everyday tasks, 2) *multimodality* – language in addition to the egocentric video to allow language-based human-agent interaction.

EgoTV also aims to enable the systematic study of generalization in task verification (see Table 1). To this end, we create the EgoTV dataset using a photo-realistic simulator AI2-THOR [29] – as a rich testbed for future research on generalizable agents for task tracking and verification. Our synthetic dataset serves as a valuable proxy of real-world performance of various task verification models while providing control over various factors affecting task reasoning.

Lastly, we also create a real-world task verification dataset (§ 4) using the CrossTask dataset [82]. While this dataset is not egocentric and is limited in its ability to systematically evaluate the generalization of task reasoning models, it enables the testing of task verification models in real world.

3.1. Definitions

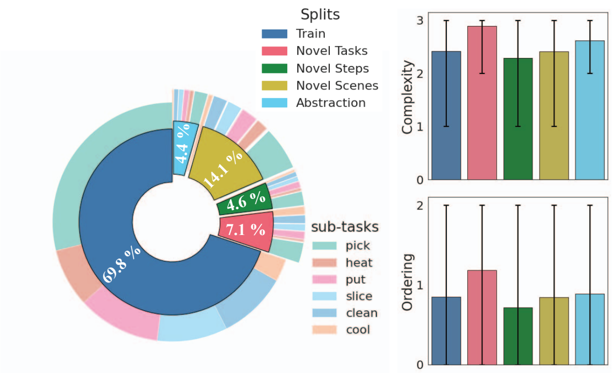
Benchmark. The objective is to determine if a task described in natural language has been correctly executed by the agent in a given egocentric video.

Tasks. Each task in EgoTV consists of multiple *partially-ordered sub-tasks* or steps. A sub-task corresponds to a single object interaction via one of the six actions: *heat, clean, slice, cool, place, pick*, and is parameterized by a *target* object of interaction[1]. By using the "actionable" properties of objects in AI2-THOR [29], we ensure that the sub-tasks are parameterized with appropriate target objects in EgoTV, e.g., *heat(book)* will never occur.

Real-world tasks consist of sub-tasks with ordering constraints, either due to physical restrictions (e.g., picking up a knife before slicing) or task semantics (e.g., slicing vegetables before frying). We allow EgoTV tasks to be partially ordered, with some steps following strict ordering, e.g. *pick* sub-task happens before *place* sub-task, while others are order-independent.

The ordering constraints between sub-tasks are captured in the task description using specifiers such as *and*, *then*, and *before/after*. For simplicity, we will refer to a task using $\langle$*sub-task*$\rangle$ _ $\langle$*ordering-specifier*$\rangle$ notation, irrespective of the actual task description. Such tasks can then be instantiated by specifying an $(object)$ of interaction. An example task instance from EgoTV: *heat_then_clean(apple)* is shown in Fig. 1 with its NL description: "apple is heated,

[1]Except the *place* sub-task, which is additionally parameterized by a *receptacle* object, we currently limit our EgoTV dataset to sub-tasks involving only a single target object.



(a) Inner Level: Distribution of tasks in each split
Outer Level: Distribution of sub-tasks within each split

(b) Top: Complexity=# sub-tasks
Bottom: Ordering=# orderings-constraints

Figure 2. **EgoTV dataset.** Sub-tasks and tasks, including their difficulty measures (§ 3.2.2) are shown per split. Novel Scenes have more tasks since all the train tasks are repeated in unseen scenes. Likewise, complexity and ordering are higher in Novel Tasks due to the addition of unseen sub-tasks.

then cleaned in a sinkbasin". The task consists of two ordered sub-tasks: heat $\rightarrow$ clean on *target* object: apple. We adopt this terminology from ALFRED [57].

3.2. Dataset

As shown in Fig. 1, EgoTV dataset consists of (task description, video) pairs with positive or negative task verification labels. By combining the six sub-tasks *heat, clean, slice, cool, put, pick* with different ordering constraints, we create 82 tasks for EgoTV (see Appendix 8.3 for an exhaustive list). Tasks are instantiated with 130 target objects (excluding visual variations in shape, texture, and color) and 24 receptacle objects, totaling 1038 task-object combinations. These are performed in 30 different kitchen scenes. We also provide comprehensive annotations for each video, including frame-by-frame breakdowns for sub-tasks, object bounding boxes, and object state information (e.g., *hot, cold, etc.*) to facilitate future research.

3.2.1 Generation

Task-video Generation. We generate the videos in our dataset by leveraging the ALFRED setup [57]. ALFRED allows us to specify the EgoTV tasks using Planning Domain Definition Language (PDDL) and then to generate plans for achieving these tasks using the Metric-FF planner [23]. We execute these plans using the AI2-THOR simulator and obtain their corresponding videos. Further details on encoding tasks using PDDL and planning are in Appendix 8.1.

Task-description Generation. We convert the plans generated for each task into positive and negative task descriptions using templates. Appendix 8.2 provides details on the process and example templates.

3.2.2 Evaluation

Metrics. We use accuracy and F1 to measure the efficacy of models on EgoTV task verification benchmark. To capture the difficulty of tracking and verifying tasks, we introduce two measures: (1) *Complexity*: measuring the number of sub-tasks in a task, which impacts the video length and requires higher action and object grounding, and (2) *Ordering*: measuring the number of ordering constraints in a task and measures the difficulty of temporal reasoning required to track and verify tasks. We evaluate model scalability by testing on tasks with varying complexity and ordering.

Generalization. EgoTV dataset enables systematic exploration of generalization in task tracking and verification via four test splits that focus on generalization to novel steps, tasks, visual contexts/scenes, and abstract task descriptions.

- **Novel Tasks**: Unseen compositions of seen sub-tasks. For e.g., if train set is $\{$*clean(apple)*, *cool(apple)*$\}$, then this test split would contain tasks like: $\{$*clean_and_cool(apple)*, *clean_then_cool(apple)*, *cool_then_clean(apple)*$\}$.
- **Novel Steps**: Unseen compositions of sub-task actions and target objects. For e.g., if the train set is $\{$*clean(apple)*, *cool(egg)*, *clean_and_cool(tomato)*$\}$, then this test split would contain tasks like: $\{$*clean(egg)*, *cool(apple)*, *clean_and_cool(apple)*$\}$.
- **Novel Scenes**: This test split contains the same tasks as in the train set. However, the tasks are executed in unseen kitchen scenes.
- **Abstraction**: Abstract task descriptions, which lack the low-level details of the task. For instance, for a *heat_and_clean(apple)* task, the full task description in the train set could be "apple is heated in a microwave and cleaned in sink basin", while the abstract task description in this split could be "apple is heated and cleaned".

Note that all the test splits and the train set are disjoint from each other. Novel Steps split tests an EgoTV model's ability to understand generalizable object affordances and tool usage. For instance, once a model learns the *slice* action on an apple, this split tests if the model can apply it to an orange. On the other hand, the Novel Tasks split tests the generalization of a model's temporal and causal reasoning capabilities on unseen compositions and orderings of known sub-tasks. Existing real-world datasets like Ego4D [17] and EPIC-KITCHENS [10] fail to provide such systematic control and precise diagnostics across various relevant yet independent factors affecting task reasoning.

3.2.3 Statistics

EgoTV dataset consists of 7,673 samples (train set: 5,363 and test set: 2,310). The split-wise division is Novel Tasks:

540, Novel Steps: 350, Novel Scenes: 1082, Abstraction: 338. The total duration of the egocentric videos in the EgoTV dataset is 168 hours, with an average video length of 84 seconds. To ensure diversity, each task in EgoTV is associated with ≈10 different task description templates (inclusive of positive and negative scenarios). We also keep an additional template set for the abstraction split. The task descriptions consist of 9 words on average, with a total vocabulary size of 72. On average, there are 4.6 sub-tasks per task in the EgoTV dataset, and each sub-task spans approximately 14 frames. Additionally, there are 2.4 ways to verify a task. This requires the virtual agent to understand all possible temporal orderings between sub-tasks from the task description for successful task verification. Real-world datasets mainly focus on recognizing actions, objects, and state changes [17, 10] without this ambiguity. Figure 2 shows a comparison of train and test splits (more analysis in Appendix 8.3).

4. CrossTask Verification (CTV) Dataset

Drawing from the EgoTV dataset, we introduce CrossTask Verification (CTV) dataset, using videos from the CrossTask dataset [82], to evaluate task verification models on real-world videos. In CTV, we prioritize assessing real-world performance of task verification models over systematic study of their generalization capabilities, unlike EgoTV. Thus, CTV complements EgoTV dataset – CTV and EgoTV together provide a solid test-bed for future research on task verification.

4.1. Dataset Generation

Like EgoTV, CTV consists of paired task descriptions and videos for task verification. CrossTask has 18 task classes, each with roughly 150 videos, from which we create ≈ 2.7K samples. We generate task descriptions by concatenating action step annotations in CrossTask. The model's objective is to determine whether the action steps (sub-tasks) and their sequence in the video align with the description. See Appendix 9 for dataset construction details.

4.2. Evaluation

Metrics. Following EgoTV, we use accuracy and F1 to measure the efficacy of the models on the CTV dataset.

Generalization. We construct a test set using videos with seen action steps but in previously unseen compositions. To ensure novel compositions, we train on videos with up to 3 action steps and test on those with 4, as illustrated in Figure 3. While this mirrors the Novel Task split in EgoTV, the CTV test set also contains unseen visual contexts (videos) – a result of limited control during dataset creation.

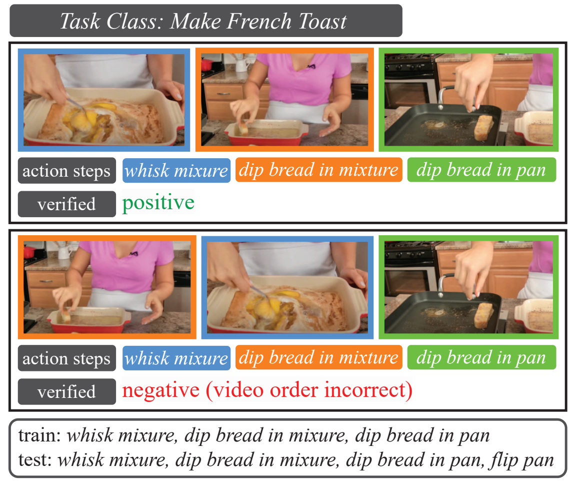


Figure 3. **CrossTask Verification (CTV) dataset.**

5. Neuro-Symbolic Grounding (NSG)

EgoTV requires visual grounding of task-relevant entities such as actions, state changes, etc. extracted from NL task descriptions for verifying tasks in videos. To enable grounding that generalizes to novel compositions of tasks and actions, we propose the Neuro-symbolic Grounding (NSG) approach. NSG consists of three modules: a) semantic parser, which converts task-relevant states from NL task descriptions into symbolic graphs, b) query encoders, which generate the probability of a node in the symbolic graph being grounded in a video segment, and c) video aligner, which uses the query encoders to align these symbolic graphs with videos. NSG thus uses intermediate symbolic representations between NL task descriptions and corresponding videos to achieve compositional generalization.

5.1. Queries for Symbolic Operations

To encode tasks, NSG captures task-relevant visual and relational information in a structured manner via symbolic operators called *queries*. For instance, the task description *heat an apple* can be symbolically captured by the query: `StateQuery(apple, hot)`. Similarly, the task description *place steak on grill* can be captured by `RelationQuery(steak, grill, on)`, which represents the relation (`on`) between objects `steak` and `grill`. Queries are characterized by *types* and *arguments* and are stored in a text format. Table 2 shows the various query types and their arguments. Different query types capture different aspects, e.g., attributes, relations, etc., thereby enabling a rich symbolic representation of everyday tasks.

5.2. Semantic Parser for Task Descriptions

The symbolic operators, i.e., queries, allow the semantic parser to represent a task's partial-ordered steps using a symbolic graph. Specifically, the parser translates a NL task

Query Type	Signature	Semantics
`StateQuery`	(Object, State), Video $\mapsto \mathbb{P}$	Queries the state (`hot`, `cold`, `clean`, `ripe`) of object in a video and returns the probability of the object state being detected. Example instructions: *heat an apple, clean a spoon*.
`RelationQuery`	(Object, Object/Receptacle, Relation), Video $\mapsto \mathbb{P}$	Queries the relation between two objects or an object and a receptacle in a video and returns the probability of the relation being detected. Example instructions: *put apple in basket*, *place spoon to the left of plate*.
`ActionQuery`	(Subtask, *Objects, *Relation), Video $\mapsto \mathbb{P}$	Queries for a sub-task with one or more arguments ($*$) in a video and returns the probability of the sub-task being executed. Example instructions: *whisk mixture, pour lemonade into glass*.

Table 2. **NSG's query types for task verification in EgoTV and CTV.** The query types `StateQuery` and `RelationQuery` are used in EgoTV, whereas `ActionQuery` is used in CrossTask. Each query type τ is modeled using a neural network f^{θ_τ} accepts unique arguments (a) and video frames (v) as input and generates an output probability $\mathbb{P} = f^{\theta_\tau}(a, v)$ of the *query* being true in the video v.

description into a graph $G(V, E)$, where a vertex $n_i \in V$ represents a query and an edge $e_{ij} : n_i \to n_j \in E$ is an ordering constraint indicating that n_i must precede n_j (Figure 4a). We experiment with two different methods to parse language descriptions of tasks to graphs – (i) finetuning language models and (ii) few-shot prompting of language models. For details, refer to Appendix 10.2. We perform a topological sort with the graph G and generate all the possible sequences of queries consistent with the sort. For example, the topological sorting of the graph in Figure 4(a) yields two ordered sequences: (n_0, n_1, n_2, n_3), (n_0, n_2, n_1, n_3). Note that this does not include all physically possible ways to complete a task, but a super-set of all possible sequences of task-relevant queries, including some infeasible sequences[2]. However, this super-set is useful because a task can be verified as accomplished if any sequence in this set can be ascertained to occur in the video.

Notably, all EgoTV tasks map to acyclic graphs through temporal disambiguation. While this can support tasks with repeated actions, such as: (Task) *pick two apples*; (Graph) pick(apple) $\to$ pick(apple); tasks that require (recursively) repeating action sequences until a desired state is reached, might result in cyclic graphs. Examples include unstacking an arbitrary number of dishes or searching for an ingredient. While currently absent in EgoTV, extending to such tasks would be a valuable future direction.

5.3. Query Encoders for Grounding

Query Encoders are neural network modules that evaluate whether a query is satisfied in an input video. Specifically, a query encoder f^{θ_τ} for a query n of type τ (e.g., `StateQuery`, `RelationQuery` etc.), accepts NL arguments (a) corresponding to objects and relations in n and a video (v) to generate the probability $\mathbb{P} = f^{\theta_\tau}(a, v)$ of the desired query being true in the video. Learnable parameters corresponding to different query type encoders in an NSG model are jointly represented as $\theta = \bigcup_\tau \theta_\tau$.

Both the text arguments a of the query and the frames of the input video v are encoded using a pre-trained CLIP encoder [50]. The token-level and frame-level representations from CLIP are separately aggregated using two LSTMs [22] to obtain aggregated features for a and v, respectively. These features are then fused and passed through the neural network f^{θ_τ} to obtain the probability $\mathbb{P}$ of the query being true in the video (see Figure 4a).

5.4. Video Aligner for Task Verification

This module of NSG must align the graph representation G of the task (generated by the semantic parser) with the video. To that end, it first segments the video, then jointly learns a) the query encoders, which detect the queries in the video segments and b) the alignment between video segments and the query sequences obtained from the topological sort on G. Such joint learning is required since the temporal locations of the queries in the video are unknown a priori requiring simultaneous detection and alignment. If the video is a positive match for the task encoded in G, at least one of the query sequences from G must temporally align perfectly with the video segments for successful task verification. Conversely, for negative matches, no query sequence from G would *completely* align with the video segments. Going forward, we use $\langle\rangle$ and $()$ to denote ordered pairs and sequences, respectively.

Video Segmentation: The video is segmented into non-overlapping segments[3] with a moving window of arbitrary, but fixed size k[4]

Joint Optimization: The objective of the optimization is to jointly learn the *alignment* Z between queries and video segments along with the *query encoders* f^θ. Given: a) the

[2]For instance, in Figure 4a, n_1 and n_2 are at the same topological level, but the sub-task in query n_1 could invalidate pre-conditions for n_2. Hence, a physically plausible task requires n_2 followed by n_1 and not vice versa. Note that EgoTV does not have physically implausible tasks.

[3]Since pretrained, off-the-shelf video segmentation models are limited to predefined action classes [13] or reliant on background frame change detection [73] and require downstream finetuning [15], we leave their integration in NSG as future work.

[4]If required, the last segment is zero-padded to k frames.

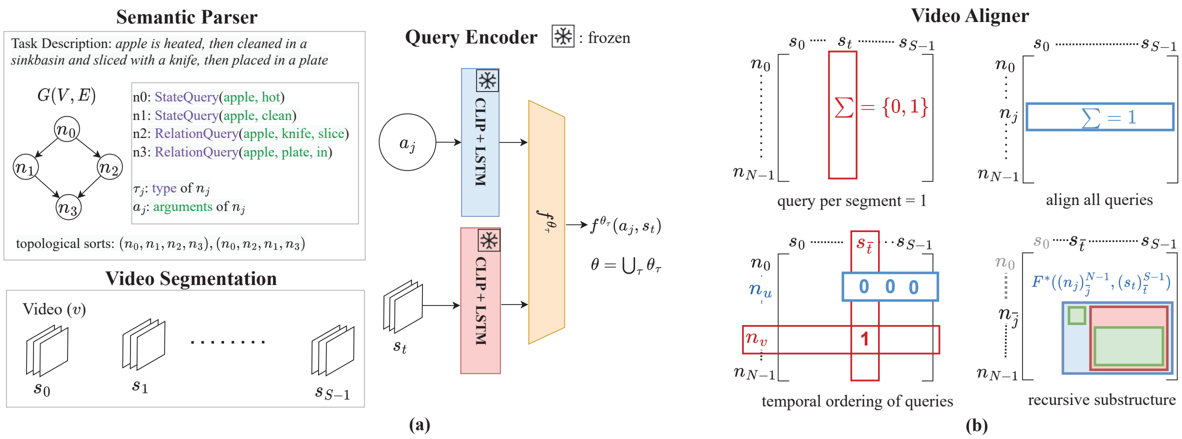


Figure 4. **NSG model** (a) semantic parser converts NL descriptions into a graph G of symbolic queries; query encoders f^{θ_τ} detect queries in individual video segments s_t; and a video aligner aligns G with video segments by computing alignment matrix Z via a constrained optimization problem (Eq. 3). (b) The constraints (Eqs. 3a 3b 3c) and the recursive structure (Eq. 4) enabling use of DP to solve for Z. Here, the blue box denotes $F^*((n_j)_{\bar{j}}^{N-1}, (s_t)_{\bar{t}}^{S-1})$, the green boxes denote $\log f^\theta(a_{\bar{j}}, s_{\bar{t}}) + F^*((n_j)_{\bar{j}+1}^{N-1}, (s_t)_{\bar{t}+1}^{S-1})$, and the red box denotes $F^*((n_j)_{\bar{j}}^{N-1}, (s_t)_{\bar{t}+1}^{S-1})$.

temporal sequence of S segments $(s_t)_{t=0}^{S-1}$ with each s_t spanning k image frames; and b) a sequence of N queries $(n_j)_{j=0}^{N-1}$ from the topological sort on G, the alignment Z is defined as a matrix $\mathrm{Z} \in \{0,1\}^{N\times S}$, where $Z_{jt} = 1$ implies that the j^{th} query n_j is aligned the video segment s_t. An example alignment with $N = 2$ and $S = 3$ is given by the matrix $\mathrm{Z} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}$, where the rows are ordered queries (n_0, n_1), the columns are temporal segments (s_0, s_1, s_2), and $\langle n_0, s_0\rangle$, $\langle n_1, s_2\rangle$ are the aligned pairs. Assuming segmentation guarantees sufficient segments for query alignment: $S \geq N$. Using Z and f^θ, the task verification probability p^θ can be defined as:

$$p^\theta = \sigma\left(\max_{\mathrm{Z}\in\{0,1\}^{N\times S}} \frac{1}{N}\sum_{j,t} \log f^\theta(a_j, s_t) Z_{jt}\right) \tag{1}$$

Here σ is the sigmoid function, $f^\theta(a_j, s_t)$ denotes the probability of querying segment s_t using query n_j with arguments a_j (§ 5.3), and $\max$ operator is over the best alignment Z between N queries and S segments. We use the ground-truth task verification label y to compute Z and f^θ by minimizing the following loss:

$$\min_\theta \frac{1}{|\mathcal{D}|}\sum \mathcal{L}_{\text{BCE}}(p^\theta, y), \tag{2}$$

here $|\mathcal{D}|$ is the EgoTV dataset size and $\mathcal{L}_{\text{BCE}}(\cdot)$ is the binary cross entropy loss computed over $|\mathcal{D}|$ input, output pairs. Given the minimax nature of Eq. 2, we use a 2-step iterative optimization process: (i) find the best alignment Z between queries and segments with fixed query encoder parameters θ (optimize Eq. 1 with fixed f^θ); (ii) optimize θ using Eq. 2, given Z.

Dynamic Programming (DP)-based Alignment: Finding the best Z in Eq. 1 given θ requires iterating over combinations of N queries and S segments while respecting certain constraints. The constraints, visualized in Fig. 4b, ensure that a) no two queries are aligned to the same segment[5] (Eq. 3a), b) all queries are accounted for in S (Eq. 3b), and c) the temporal orderings between queries in the query sequences are respected (Eq. 3c). Specifically, if query n_u precedes n_v ($n_u \to n_v$), and query n_v is paired with segment $s_{\bar{t}}$ (i.e. $Z_{v\bar{t}} = 1$), then query n_u cannot be paired with any segment that lies after $s_{\bar{t}}$ (i.e. $Z_{ut} \neq 1\ \forall\ t \geq \bar{t}$). The resulting optimization problem for Z, given θ is:

$$\max_{\mathrm{Z}\in\{0,1\}^{N\times S}} \sum_{j,t} \log f^\theta(a_j, s_t) Z_{jt}, \quad \text{s.t.} \tag{3}$$

$$\sum_{j=0}^{N-1} Z_{jt} \in \{0,1\}, \quad \forall\ 0 \leq t \leq S-1 \tag{3a}$$

$$\sum_{t=0}^{S-1} Z_{jt} = 1, \quad \forall\ 0 \leq j \leq N-1 \tag{3b}$$

$$n_u \to n_v,\ Z_{v\bar{t}} = 1 \implies Z_{ut} \neq 1, \quad \forall\ t \geq \bar{t} \tag{3c}$$

Intuitively, the solution to Eq. 3 gives us the best alignment score (note, the overlap with Eq. 1). The iterations over N queries and S segments for solving Eq. 3 are underpinned by an overlapping and optimal substructure. For instance, to optimally align queries $(n_j)_{j=0}^{N-1}$ and segments $(s_t)_{t=0}^{S-1}$, one could: a) pair $\langle n_0, s_0\rangle$ and optimally align the remaining queries and segments $(n_j)_{j=1}^{N-1}, (s_t)_{t=1}^{S-1}$; or (2)

[5] This ensures that the order of queries can be verified, which cannot be done when queries belong to the same segment.

skip s_0 and still optimally align *all* queries, now with the remaining segments $(n_j)_{j=0}^{N-1}, (s_t)_{t=1}^{S-1}$ (see Fig. 4b(iv)). This recursive substructure leads to a DP solution for Eq. 3.

Let, $F^*((n_j)_{\bar{j}}^{N-1}, (s_t)_{\bar{t}}^{S-1})$ denote the best alignment score for queries $(n_j)_{\bar{j}}^{N-1}$ and segments $(s_t)_{\bar{t}}^{S-1}$ from Eq. 3. Based on the aforementioned reasoning, $F^*((n_j)_{\bar{j}}^{N-1}, (s_t)_{\bar{t}}^{S-1})$ can be recursively written as:

$$F^*((n_j)_{\bar{j}}^{N-1}, (s_t)_{\bar{t}}^{S-1}) = \max\big(\log f^\theta(a_{\bar{j}}, s_{\bar{t}}) \\ + F^*((n_j)_{\bar{j}+1}^{N-1}, (s_t)_{\bar{t}+1}^{S-1}), F^*((n_j)_{\bar{j}}^{N-1}, (s_t)_{\bar{t}+1}^{S-1})\big) \quad (4)$$

The base cases for the DP are: (i) $\mathrm{Z} = \mathbb{I}$ if $N = S$; (ii) $Z_{jt} = 1 \ \forall \ t$ if $j = N - 1$. It is worth noting that the DP subproblems, together with the base cases, satisfy the constraints in Eq. 3a 3b 3c. Since the video may match any of the sequence in the super-set of query sequences (from the topological sort on G), we repeat this process of computing F^* for each sequence and select the maximum value.

Optimizing Query Encoder Parameters θ: After obtaining the best alignment Z using DP, we substitute the corresponding value of $F^*((n_j)_{j=0}^{N-1}, (s_t)_{t=0}^{S-1})$ in Eq. 1 and subsequently Eq. 2. In Eq. 2, we use single mini-batch of training examples and take one gradient-update step of the Adam optimizer for the query encoder parameters θ.

6. Experiments

We compare various state-of-the-art (SOTA) VLMs with NSG on the EgoTV benchmark (see Appendix 10.1 for NSG's experimental training details).

6.1. SOTA VLM Baselines

We investigate 6 VLMs developed for video-language tasks requiring similar reasoning as EgoTV. Summarized in Table 3, **CLIP4Clip** [39], **CLIP Hitchhiker** [3], **CoCa** [76] use image backbones followed by temporal aggregation, while **VideoCLIP** [36], **MIL-NCE** [44], and **VIOLIN** [38] use video backbones. With the exception of CoCa, which is trained with contrastive and captioning loss, all other models are trained using contrastive loss [44]. Lastly, VideoCLIP and VIOLIN use an explicit fusion of text-vision features. For each model, we freeze all pretrained feature extractors and finetune a fully-connected probe layer, along with the temporal aggregation layers where appropriate (CLIP4Clip-LSTM, VIOLIN), using EgoTV's train split.

Finally, to establish upper bounds on EgoTV, we instantiate: (1) a **Text2text model**, which constructs video captions using ground-truth labels for objects and actions, encodes the captions and task descriptions using (pretrained) RoBERTa model [81] and measures alignment using the cosine similarity score (see Appendix 11.2), and (2) an **Oracle model**, which is trained with full supervision on sub-tasks labels and locations in addition to task verification labels.

6.2. Results

In Table 3, we show the performance of NSG vs. SOTA VLMs per split of EgoTV. (1) **Novel Tasks**: NSG significantly outperforms other baselines due to its ability to decompose and detect sub-tasks while using DP alignment to handle temporal constraints among them. In contrast, other baselines rely on detecting the entire task under temporal constraints, which is more challenging. Further, image-based baselines outperform video-based baselines due to their ability to capture a greater degree of compositional detail through frame-level representations. (2) **Novel Steps**: NSG's poor performance in this split could be attributed to its low precision in the *slice* sub-task (which is dominant in this split), as shown in Figure 5 [Right]. We hypothesize that since NSG only uses the aligned segments while discarding the rest, learning to utilize context from neighboring segments to capture *slice* (like picking up a knife) could be a promising future direction. (3) **Novel Scenes**: Here, NSG is comparable to the best baseline VIOLIN-ResNet. Since the tasks are identical to the train split, the success of a model is contingent on the vision encoder's ability to accurately detect the same sub-tasks in unseen scenes. Consequently, models with an additional temporal aggregation layer (VIOLIN) finetuned on EgoTV, tend to outperform image-based models that do not have temporal aggregation (CLIP Hitchhiker) and models with frozen video features (MIL-NCE, VideoCLIP). (4) **Abstraction**: NSG significantly outperforms the baselines, primarily due to its semantic parser, which captures the underlying structure of the description and encodes the relevant concepts, such as objects and sub-tasks, to generate an (abstract) symbolic output.

6.3. Analysis of NSG

NSG learns to localize task-relevant entities without explicit supervision. Figure 5 shows the confusion matrix of `StateQuery` & `RelationQuery` outputs, which capture sub-tasks, with their ground truths. The high recall demonstrates NSG's ability to localize task-relevant entities, despite being trained using only task verification labels.

Effect of query types on NSG. While query types with multiple entity arguments might appear capable of modeling complex dependencies amongst entities and having more expressive power, encoding multiple entities jointly using a single encoder makes the grounding problem more challenging. Hence, in practice, we found that using a combination of `StateQuery` & `RelationQuery` types as opposed to `ActionQuery` (which encodes multiple entities using a single encoder) enabled better grounding and led to better performance in terms of F1-score (Table 4).

NSG shows consistent performance with increasing task difficulty. In Figure 5, NSG's performance is minimally affected by increase in task difficulty characterized by number of sub-tasks (complexity) and ordering constraints (§ 3.2.2)

Model	Visual feature	Text feature	MM Fusion	Novel Tasks	Novel Steps	Novel Scenes	Abstraction	Average
Text2text [81]		RoBERTa		64.9	65.8	66.5	64.7	65.5
CLIP Hitchhiker [3]	CLIP(I)	CLIP		43.9	66.5	72.2	13.6	49.1
CLIP4Clip mean [39]	CLIP(I)	CLIP		49.3	70.9	74.9	16.1	52.8
CLIP4Clip seqLSTM [39]	CLIP(I)	CLIP		56.2	73.2	74.6	17.5	55.4
CoCa [76]	Tx(I)	Tx	Y	51.5	71.6	71.9	43.5	59.6
VIOLIN-ResNet [38]	ResNet(I)	BERT	Y	47.4	**80.4**	**85.6**	42.5	64.0
MIL-NCE [44]	S3D(V)	Word2vec		30.5	69.6	73.5	24.3	49.5
VideoCLIP [36]	Tx(V)	Tx	Y	29.3	67.6	77.9	25.6	50.1
VIOLIN-I3D [38]	I3D(V)	BERT	Y	45.6	79.7	83.9	47.6	64.2
NSG (ours)	CLIP(I)	CLIP	Y	**90.0**	64.7	84.9	**80.4**	**80.0**
Oracle Model	CLIP(I)	CLIP	Y	95.0	96.7	97.6	97.2	96.6

Table 3. **Comparison of baselines with NSG on different data splits using F1-score.** MM fusion indicates multimodal fusion of vision and text features. Tx indicates the Transformer as feature extractor with image (I) and video (V) backbones. Video backbone models are highlighted in gray. Underline indicates second-best performance.

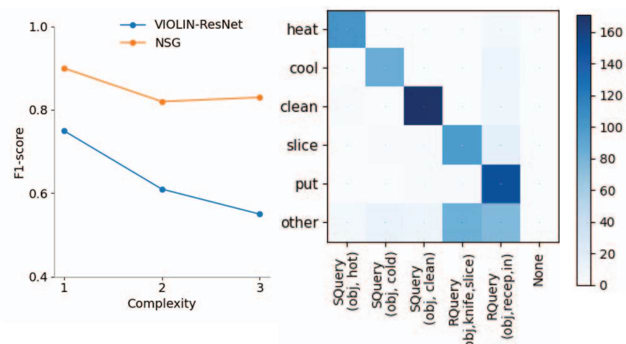


Figure 5. [Left] F1-score of NSG vs. best-performing baseline for EgoTV tasks with varying complexity averaged over all splits (Appendix 10.4 shows performance with varying ordering). [Right] Confusion Matrix for NSG Queries on validation split (SQuery: `StateQuery`, RQuery: `RelationQuery`). See Appendix 10.4 for results on all splits.

NSG	Novel Tasks	Novel Steps	Novel Scenes	Abstract.
`Action`	78.2	45.6	70.6	75.5
`State+Relation`	90.0	64.7	84.9	80.4

Table 4. `(State + Relation) Query` vs. `ActionQuery`

unlike the best-performing baseline (VIOLIN-ResNet).

NSG is robust to segmentation window size The effect of k on NSG is minimal (Appendix 10.4).

NSG also enables task verification on real-world data. NSG outperforms all competitive baselines on CTV significantly with F1-score (NSG: **76.3**, CoCa: 70.9, VideoCLIP: 49.7, VIOLIN 34.7), demonstrating its causal and compositional reasoning capabilities in real-world applications (see Appendix 10.4 for details).

Limitations of NSG. (1) It does not consider multiple simultaneous actions like "picking an apple while closing the refrigerator door", (2) The assumption of equal-length video segments may be unsuitable for sub-tasks with a highly variable duration. We defer exploration of these limitations to future work, (3) Since NSG aligns the video with the entire task graph, it requires the full task execution video. Without this, alignment is partial, rendering NSG ineffective for online task verification.

7. Conclusion

To address various challenges towards the development of egocentric assistants that can track and verify the accomplishment of everyday tasks, including reasoning about causal and temporal constraints in tasks, visual grounding, and compositional generalization, we introduce Egocentric Task Verification (EgoTV), a benchmark and dataset containing partially-ordered, multi-step tasks with natural language task specifications. We also present NSG, a novel neuro-symbolic approach that enables order-aware visual grounding, and demonstrate its effectiveness on both the EgoTV dataset and a real-world dataset CTV. We hope our contributions will help in advancing research on egocentric assistants that can aid users in everyday tasks.

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