

# Anticipating Object State Changes

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## Abstract

*Anticipating object state changes in images and videos is a challenging problem whose solution has important implications in vision-based scene understanding, automated monitoring systems, and action planning. In this work, we propose the first method for solving this problem. The proposed method predicts object state changes that will occur in the near future as a result of yet unseen human actions. To address this new problem, we propose a novel framework that integrates learnt visual features that represent the recent visual information, with natural language (NLP) features that represent past object state changes and actions. Leveraging the extensive and challenging Ego4D dataset which provides a large-scale collection of first-person perspective videos across numerous interaction scenarios, we introduce new curated annotation data for the object state change anticipation task (OSCA), noted as Ego4D-OSCA. An extensive experimental evaluation was conducted that demonstrates the efficacy of the proposed method in predicting object state changes in dynamic scenarios. The proposed work underscores the potential of integrating video and linguistic cues to enhance the predictive performance of video understanding systems. Moreover, it lays the groundwork for future research on the new task of object state change anticipation. The source code and the new annotation data (Ego4D-OSCA) will be made publicly available<sup>1</sup>.*

## 1. Introduction

When observing human-object interactions and object manipulations, we humans can effortlessly reason on and anticipate changes in object states [6, 21, 3]. Imagine, for example, that while preparing the table for a dinner, somebody brings a bottle of wine. Even before opening it, we can fairly easily infer that in the near future, the bottle will be “opened”, and glasses will be “filled”. Recognizing and anticipating object states and their changes is crucial for any entity that interacts with objects, because the state of an object significantly affects its physical and functional properties and, therefore, plays a decisive role in further activity understanding, reasoning, and task planning.

While it is almost effortless for humans, the capability of predicting object state changes still lies beyond the competencies of any current AI-powered system [38, 36]. Understanding object states and their changes in the context of actions relates to visual object perception, action/activity recognition, and object state estimation. While these individual capabilities have been heavily researched by the computer vision community, surprisingly, the problem of anticipating changes in object states remains unexplored. However, recognizing and anticipating object state changes would be an important competence of AI-powered agents that need to reason about human activities and/or perform task planning [33, 37].

Researchers have only recently started to focus on methods for the representation and understanding of object state changes in videos in the context of state-modifying actions [24, 28, 26], which can also be seen as transformations [31], while existing benchmarks largely ignore object state changes and focus on traditional types of annotations

<sup>1</sup><https://projects.ics.forth.gr/cvrl/osca/>

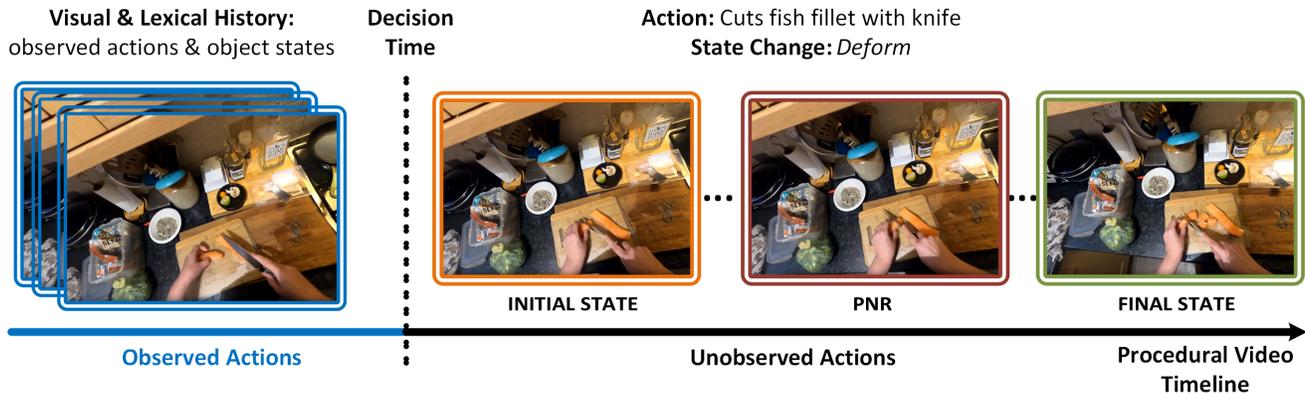


Figure 1. We introduce a new problem, that of anticipating object state changes in videos of procedural activities. At a decision point which is the start time of the next, yet unobserved action, the goal is to predict whether there will be a state change related to the next active object and, if yes, estimate its type. An object state change is defined as the transition from a pre-state (initial) to a post-state (final) that occurs at the Point of No Return (PNR) time during a state-modifying action.

related to object type, location, or shape, attributes, affordances, and human actions. The problem of Object State Classification (OSC) is defined as the multi-class recognition of an object’s state in a still image [15, 13], or the initial and final object states in videos that demonstrate state-modifying actions [14]. The binary object state change classification variant is also related to the detection of whether or not a state change has occurred in a short video clip [7, 14].

In this work, we take one step beyond Object State Classification (OSC) by **introducing the new task of visual object state change anticipation (OSCA)** in videos. OSCA focuses on the multi-class prediction of the state change to occur during the yet unseen, next action in an instructional video. Specifically, as shown in Fig. 1, at a certain decision point in time, noted as the start of the next, yet unobserved action, we aim to predict the type of state change of the next active object. The state change happens at the “Point of No Return” (PNR) [14]. Our approach may also predict that no state change will occur to the next active object in the forthcoming action which implies the anticipation of a no-state-modifying action. Our approach to tackle this new task relies on the cumulative history of recognized preceding actions and object states, up to the decision point where this prediction is performed. The integration of visual information concerning the recent past and textual description of past actions and states is a key idea to model this historical context effectively.

To assess the performance of our method for OSCA, we augment the annotations of the large-scale and challenging Ego4D dataset [14] to include labels for the initial and the final object states for state-modifying actions. This results in the Ego4D-OSCA, a variant of the Ego4D dataset that will become available to the vision community.

In summary, this work makes the following contribu-

tions:

- We introduce the new problem (OSCA) of anticipating the state change of the next active object in instructional videos.
- We propose the first solution to OSCA, leveraging visual and language features for modeling the history of performed actions, object states and their changes.
- We introduce Ego4D-OSCA, a new benchmark for evaluating solutions to the OSCA problem.

## 2. Related Work

Object states capture the dynamic aspects of object appearance and/or functionality and are subject to visually perceivable changes, as a result/effect of state-modifying actions. They are also known as object fluents related to changeable object attributes [16, 2, 17]. Object State Change Anticipation (OSCA) is a new problem introduced in this paper. As such, to the best of our knowledge, there is no prior work that addresses this problem. Below, we review research on the closely-related problems of object state classification in images and the interplay of object state estimation and human action recognition in videos.

**Object State Classification in Images:** Object states are typically considered as a special subset of “visual attributes”, i.e. visual concepts that are related to the physical and functional properties of objects [15]. Object states and their changes are perceivable by humans and should be perceivable by AI-enabled agents [8]. The majority of the approaches that address the attribute classification task follow a similar approach to that of object classification by training a convolutional neural network with discriminative classifiers on annotated image datasets [25]. Few works focus

explicitly on state classification [13], while most of them rely on the same assumptions used for the attribute classification task. A prominent research direction to tackle this task refers to zero-shot learning that gained considerable attention in recent years due to its practical significance in real-world applications, mitigating the problem of collecting and learning training data for a very large number of object classes [34]. One prevalent zero-shot learning approach involves the utilization of semantic embeddings to represent objects and their attributes in a low-dimensional space [32]. The work in [12] leverages Knowledge Graphs (KGs) and semantic knowledge in the context of zero-shot object classification. In a similar vein, the work in [11] combines KGs and Large Language Models (LLMs) in order to address object-agnostic state classification. A recent work by [24] focuses on the recognition of object states based on the concept of compositional generation of novel object-state images, while the recently proposed method in [28] introduced a novel conditioned diffusion model that focuses on generating temporally consistent and physically plausible images of actions and object state transformations based on an input image and a text prompt describing the targeted transformation.

**Object State Change Estimation and Action Recognition in Videos:** Object state changes have been considered a meaningful information source in the task of video-based human action understanding and recognition (HAR). Human actions frequently induce modifications in the states of associated objects, thereby influencing the overall dynamics of action sequences. Understanding the causal relationships between actions and object states has the potential to enrich our comprehension of action dynamics throughout long complex activities in procedural/instructional videos. Therefore, in HAR, object state changes are often considered complementary attributes to the visual representation of actions. These changes are typically derived within the visual domain through the utilization of explicit models for object detection and state estimation [9, 26, 18], or indirect modeling of object states based on general scene changes resulting from action execution [1, 5, 4]. Several methods exploit object states implicitly to estimate the type of action performed. The work in [1] was among the first to propose a method to automatically discover object states and the associated manipulation actions from videos by leveraging a discriminative clustering framework that jointly models the temporal order of object states and manipulation actions. The work in [17] explored the recognition of object fluents (changeable attributes of objects) and tasks (goal-oriented human activities) in egocentric videos using a hierarchical model that represents tasks as concurrent and sequential object fluents. Moreover, [19] focuses on understanding human actions within videos by analyzing complex interactions across multiple interrelated objects by recognizing

different states changes of these objects. In [27, 26] a multi-task self-supervised framework is proposed that allows the temporal localization of object state changes and state-modifying actions in uncurated web videos. Furthermore, [35] introduced the novel VidOSC approach for understanding object state changes by segmenting object parts related to those changes in videos from an open-world perspective. A recently proposed framework [22] can recognize object-centric actions by relying only on the initial and final object states. The model is also able to generalize across unseen objects and different video datasets. The method proposed in [23] aims at disentangling visual embeddings that distinctly represent object states alongside identities, enabling effective recognition and generation of novel object-state compositions through a compositional learning framework. Finally, the InternVideo [7] video foundation model was adapted to tackle the tasks of object state change classification and action anticipation in the context of the Ego4D Challenges.

### 3. Methodology

The proposed framework, depicted in Fig. 2, draws inspiration from the efficacy of amalgamating visual and lexical information for semantic action/activity encoding. Pursuant to this objective, it adopts a three-stream architecture. Within this design, a visual encoding module is tasked with capturing the visual attributes of the ongoing actions, while two lexical-based encoders are employed to extract the semantic nuances from a procedural-oriented representation of past actions and object states. The framework orchestrates the fusion of these distinct representations towards a unified objective: **the anticipation of the next object state**. This anticipatory task entails the estimation of the forthcoming state in which the object of interest will reside during the subsequent action. By integrating visual and lexical cues, the framework endeavors to holistically capture the underlying dynamics and contextual intricacies governing object-state transformations across sequential action.

The design of our framework draws from the recent VLMAH model [20] that was specifically tailored for the task of *action* anticipation. We augment this architecture by introducing specialized object state history encoding modules. Additionally, we redesign the action history module to facilitate disjoint encoding, capturing both the motion motifs in actions (verbs) and the transitions of objects-in-use (nouns) between actions. This refined architecture enables a more nuanced representation of the sequential dynamics between actions and object states, empowering the framework to achieve enhanced performance in the task of next-state anticipation within dynamic environments.

As illustrated in Fig. 2, the proposed framework consists of two primary components: (a) the current action and object state estimation module, and (b) the object state antic-

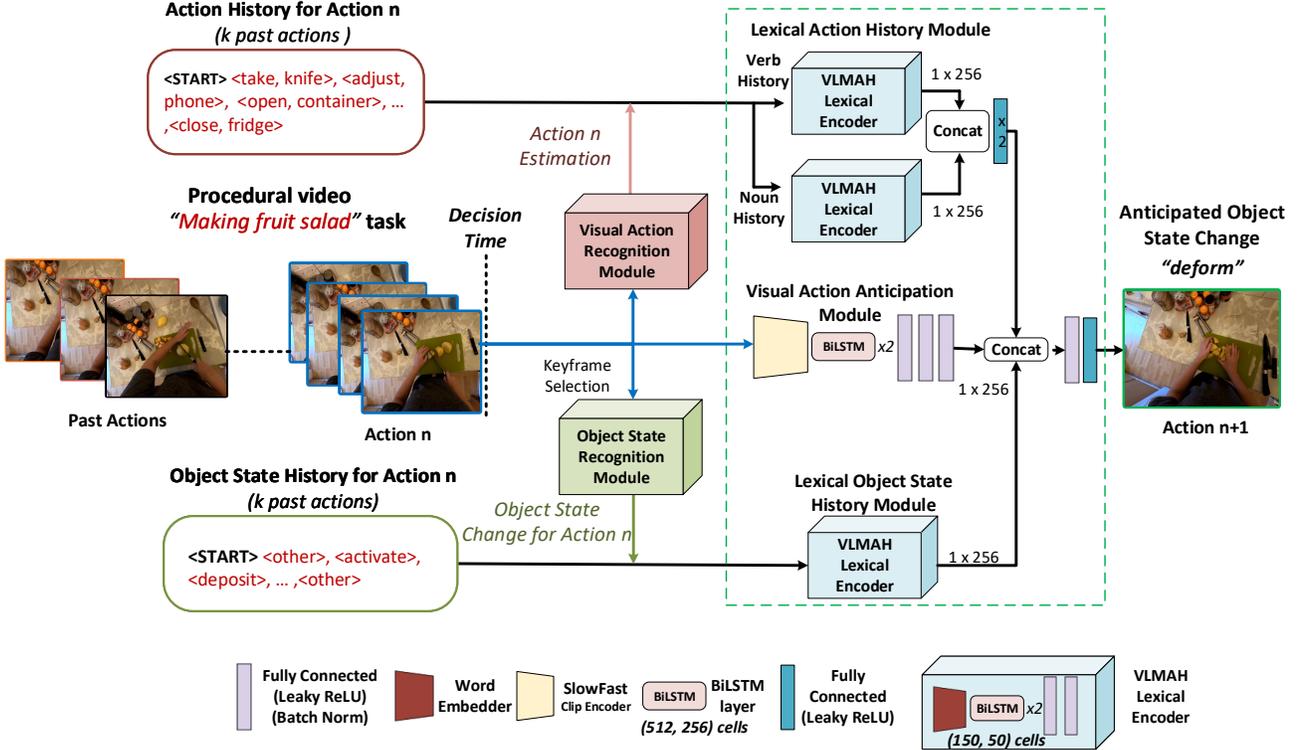


Figure 2. Overview of the proposed baseline framework for the object state change anticipation task. The proposed framework anticipates object state changes by integrating real-time visual data and a historical record of past actions and object states changes.

ipation module, depicted within the thin-dotted rectangle. Our contribution resides in (a) the conceptualization of this framework and (b) the development of the object state anticipation module. Concerning the latter, it encompasses the following constituent components.

**Visual Encoder:** In the visual encoding module, we employ a lightweight visual encoder consisting of a single-branch bidirectional long short-term memory (BiLSTM) component followed by a multi-layer perceptron (MLP). We selected this simplified design for the visual encoder due to its primary objective of temporally encoding the enduring relationships among encoded short-term segments extracted from the input video. Our model relies on an external pretrained human action recognition model, such as SlowFast [10] or TSN [30] to provide encodings of short-term spatio-temporal dependencies between the frames inside a single segment.

**Action & State History Encoders:** As illustrated in Fig. 2, both encoders exploit the model design of the lexical encoder of the VLMAH model [20], which follows a NLP neural network design consisting of BiLSTM and MLP components. The decision to employ a simple NN for encoding the history, instead of utilizing LLMs was motivated by several factors. Firstly, the computational efficiency of LLMs such as GPT-3 or LLaMA, often entails significant resource requirements for training and inference [29],

whereas a simpler neural network architecture mitigates computational overhead. Secondly, LLMs are pre-trained on general text corpora and may not capture the domain-specific nuances inherent in the textual data related to action histories and object states. Additionally, the simplicity of the chosen architecture facilitates interpretability, data efficiency, and customization, affording greater control over the model’s behavior and adaptation to the task’s requirements.

**Learning Objective:** The learning objective for training the model was exclusively focused on evaluating the anticipated state estimate. This deliberate choice stemmed from the desire to prioritize the accurate prediction of object states, which constituted the primary objective of the study. This objective was formulated using the cross-categorical entropy loss, which is well-suited for multi-class classification tasks, such as predicting object states across different categories:

$$\mathcal{L} = -\frac{1}{N} \sum_{i=1}^N \sum_{c=1}^C y_{i,c} \log(\hat{y}_{i,c}), \quad (1)$$

where  $N$  is the number of samples in the dataset,  $C$  is number of object state categories,  $y_{i,c}$  is the ground truth next state label for the object-in-use in the current action sample  $i$  and  $\hat{y}_{i,c}$  is the predicted next state probability.

During training, the proposed framework leverages oracle action and state detectors to provide the action and state

history, respectively, for each clip in the dataset (see Fig. 2). These detectors estimate the current action and object state observed in the clip, serving as ground truth annotations for training purposes. However, it is important to note that in a complete inference mode where the model is deployed for real-world applications, there is a requirement for current action and current object state recognition models to provide input to the framework. Consequently, our proposed model is solely tasked with the learning objective of next object anticipation during training, focusing exclusively on predicting the future state of the object. By decoupling the training and inference phases in this manner, the model is able to effectively learn the dynamics of object state transitions without the added complexity of simultaneously predicting the current action.

## 4. Experimental Setup

**The proposed Ego4D-OSCA dataset:** We introduce Ego4D-OSCA as a new partition of the large-scale Ego4D dataset that aims to serve as a benchmark for the assessment of methods for object state change anticipation. The volume and diversity of the Ego4D dataset make Ego4D-OSCA a very challenging dataset for OSCA, as shown in Fig. 3. Ego4D-OSCA is tailored for the long-term activity (LTA) prediction benchmark, which aims to forecast the sequence of activities that will unfold in future video frames. Due to an ongoing challenge, the official test set for this benchmark has not yet been released, prompting us to repurpose the validation split as a stand-in test set. To enrich the LTA benchmark, we have integrated object state annotations extracted from the dataset as follows.

The original Ego4D dataset does not include annotations for the specific state labels of individual video frames. Instead, annotations about state changes are provided, which relate to entire video segments. Additionally, the dataset includes annotations for bounding boxes and object classes across seven critical frames within each video segment. These frames are temporally centered around the occurrence of the state change that occurs within each video segment. Based on this information, we super-annotate certain critical frames of each video segment with state-related labels as follows. For each video segment, we annotate the initial and final frames as  $pre\_X$  and  $post\_X$ , respectively, where  $X$  denotes the label of the state change. Furthermore, in line with the semantic implications of these changes, we establish three pairs of state changes. Each pair is constructed under the premise that the first action is the inverse of the second concerning the resulting state change. For instance, if  $X$  and  $Y$  represent inverse state changes, then the labels  $pre\_X$  and  $post\_Y$  are considered samples of identical states. A similar correspondence applies between  $pre\_Y$  and  $post\_X$ . For example, the states  $pre\_remove$

and  $post\_deposit$  are considered identical, since  $remove$  and  $deposit$  constitute a pair of inverse state changes. Table 1 delineates the specifics of these super-annotated states. Moreover, Table 2 provides important dataset statistics. By incorporating these detailed annotations, Ego4D-OSCA offers researchers a comprehensive platform to explore and refine methods for anticipating object behavior and activity sequences in egocentric video contexts.

**Implementation Details:** The proposed state anticipation model (dotted rectangle in Fig. 2) is trained on a single NVIDIA TITAN GPU using the Adam optimizer, a batch size of 32, a learning rate of  $1e - 4$ , without any temporal augmentations (clip or frame cropping). Short-term associations between neighboring segments of an input video are represented using the pre-extracted SlowFast frame level features from Ego4D. Regarding the selection of the pre- and the post-state keyframes that are introduced in the object recognition model, we exploit the PNR annotations of Ego4D, which correspond to the first frame in each clip when the state change/transition is visible.

We should note that in real-world inference, the action and state lexical histories in the proposed anticipation model will be populated by existing action recognition and object state estimation models trained on respective data of the task.

## 5. Experimental Results

### 5.1. Object State Change Anticipation

In Table 3, we compare variants of an object state anticipation model, to highlight the impact of incorporating lexical histories of past actions and object states on object state anticipation performance. Starting with the vision-only model (VID-A), which solely relies on the visual representation of the current action, we observe relatively modest performance levels. However, when lexical histories of past actions are introduced through an oracle recognition model (VNLP (O-Action)), we observe a slight performance improvement, indicating the potential benefit of contextual action information. Notably, incorporating lexical histories of past object states from an oracle recognition model (VNLP (O-State)) leads to significant performance gains, that highlight the importance of considering object state dynamics in anticipation tasks. Further improvements are observed when both types of lexical histories are integrated into the model (VNLP (O-Action, O-State)), demonstrating the synergistic effect of leveraging contextual information from both actions and object states. Overall, the low anticipation scores underscore the inherently challenging nature of the task and the intricacy of the scenarios of the dataset that pose significant challenges for anticipation models.

We also performed experiments in which the oracle-



Figure 3. Six types of state-modifying actions related to two types of state transitions/changes (“deform” and “remove”), that are included in videos of the Ego4D dataset. Each action and state change occurrence is represented by a triplet of frames (pre-state, PNR, post-state). Each state change type is associated with various actions taking place in different environments and diverse scenarios, which emphasizes the complexity and the challenges introduced when dealing with the object state change anticipation (OSCA) problem.

OSC	activate	deactivate	deposit	remove	construct	deconstruct	deform	other
Pre	pre activate	pre deactivate	pre deposit	pre remove	pre construct	pre deconstruct	pre deform	pre other
Post	post activate	post deactivate	post deposit	post remove	post construct	post deconstruct	post deform	post other

Table 1. The super-annotated state change labels and the corresponding pre-/post-state labels of a video segment, where the state modifying action occurs. The pairs activate-deactivate, deposit-remove, and construct-deconstruct constitute pairs of inverse state change actions. Frame state labels that correspond to the same state are depicted with the same colour.

based state estimation was replaced with an actual object state estimator. To fulfill this requirement in our experiments, we adopted the object state classification method of [13], with minor adjustments that we elucidate below. The state history of the non-oracle model relies on the outputs of two distinct state classifiers. Each classifier receives either the first or the last frame of each video segment as input to predict the object state label for the respective frame. The prediction of the state change label for the video segment considers both outputs and is derived based on the following rules. If the object state predictions are  $pre\_X$  and  $post\_X$ , respectively, the inferred state change for the video segment is denoted as  $X$ . Conversely, if the classifiers predict  $pre\_X$  and  $post\_Y$ , where  $X$  and  $Y$  are distinct and represent inverse state changes, it is concluded that no state change has occurred. Finally, if neither of the conditions mentioned above is met, the state change prediction defaults to the output of the second classifier; i.e., if the prediction is  $post\_Y$ , the state change for the video segment is identified

as  $Y$ . For example, if the predictions of the two classifiers are  $pre\_activate$  and  $post\_activate$  the prediction for the state change would be  $activate$ . Likewise, if the predictions are  $pre\_activate$  and  $post\_deactivate$  the prediction of the state change would be that of no change.

When we replace the oracle object state recognition model with the above-described object state estimator, which showcased a mean frame-wise object state recognition accuracy of 24.1% in this dataset, we observe a significant drop in accuracy (rows 5 & 6 of Table 3). This difference in accuracy underscores the critical role of precise object state recognition in effectively anticipating future object states within dynamic environments.

## 5.2. The Impact of Object State and Action Recognition Accuracy

To further demonstrate the impact of the accuracy of the current action and current object state recognizers on the object state change anticipation task, we conducted exper-

	No OSC	activate	deactivate	construct	deconstruct	deposit	remove	deform	other
<b>Train</b>	2066	4017	1492	4186	1773	14984	15338	4400	15667
<b>Test</b>	1284	1888	617	2289	966	7613	7608	2149	8715

Table 2. Statistics for the Ego4D-OSCA dataset per object state change class. In total the dataset has 61858 training clips and 31846 testing clips.

Model	Top@1/5 mAcc
VID-A	23.93 / 89.10%
VNLP (O-Action)	25.59 / 83.06%
VNLP (State [13])	30.23 / 91.80%
VNLP (O-State)	34.35 / 85.92%
VNLP (O-Action, O-State)	<b>35.60</b> / 88.14%
VNLP (O-Action, State [13])	28.56 / <b>92.24%</b>

Table 3. Object state change anticipation performance for various model configurations (O-: Oracle recognizer, VID-A: vision-only state anticipation model).

Noise (Action, State)	Top@1/5 mAcc
(0%, 0%) (Oracle)	<b>35.60 / 88.14%</b>
(25%, 25%)	30.46 / 84.42%
(50%, 50%)	26.00 / 81.75%
(75%, 75%)	22.48 / 78.09%

Table 4. Object state change anticipation model robustness to recognizer performance variability.

iments that hypothesized recognizers of different accuracy. In this experimental setup, we uniformly introduce noise, representing erroneous estimations, to both the action and state histories, since in the inference stage of the proposed framework, these histories would need to be populated by the outputs of the respective recognizers.

Table 4 presents the results obtained under three varying levels of label noise (rows 2-5), contrasted to the outcomes achieved when employing ground truth labels (where the noise level is 0%). The noise levels correspond to the rate of erroneous estimates generated by the recognizers, i.e., 25% corresponds to a recognizer with 75% mAcc. As it can be verified based on the obtained results, the performance of the state anticipation task is influenced by the recognizer’s accuracy, demonstrating an approximate 4 – 5% reduction in OSCA accuracy for every 25% decrease in object state and action recognition accuracy. Notably, despite substantial declines in state and action recognition performance, the anticipation model exhibits only a marginal decrease in performance. This finding can be attributed to the compensatory capability of the visual component of the model, which effectively accommodates dynamic and previously unseen sequences of action and state histories.

## 6. Conclusions

We introduced the new problem of object next-state anticipation and proposed a baseline framework to address it. Our framework is a novel effort in this domain, shedding light on the potential of leveraging contextual information to enhance object state anticipation performance within vision-based models. By integrating lexical histories of past actions and object states with visual information of the recent past, our framework demonstrates notable improvements in anticipation accuracy, underscoring the importance of contextual understanding in dynamic environments. To validate the efficacy of our approach, we adapted a recent,

large-scale egocentric dataset, Ego4D [14], introducing a specialized subset for object state anticipation, referred to as Ego4D-OSCA.

An integral aspect of the proposed method involved employing a basic NLP model to handle the lexical histories of previous actions and object states. While this approach offers certain advantages, as discussed in Section 3, it is constrained by its reliance on simplistic lexical structures adhering to predefined structural protocols and language formats. We can substitute these models with LLMs to address these limitations, particularly in capturing nuanced semantics and enhancing adaptability across diverse domains and languages. However, this comes at the extra cost of increased computational and storage demands. Finally, another interesting future direction we plan to explore is studying the problem under zero-shot settings. This could lead to the possibility of developing a method that can anticipate changes that are not included in the training data, or anticipate changes that affect novel classes of objects, or occur as the effect of novel classes of actions.

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