Navigating Hallucinations for Reasoning of Unintentional Activities

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Abstract

We introduce a novel task of understanding unintentional human activities in videos, formalizing it as a reasoning problem in a zero-shot setting. Specifically, the goal is to determine why an intentional action transitions into an unintentional one. We first assess the performance of current state-of-the-art Large Multimodal Models (LMMs) on this task, observing a tendency for these models to produce hallucinated reasoning. To address this, we propose a novel prompting technique, called Dream of Thoughts (DoT), which helps the models navigate hallucinated thoughts and improve reasoning accuracy. To rigorously evaluate the models' reasoning abilities, we also introduce three specialized metrics tailored to this task. Experiments conducted on the OOPs, UCF-Crimes, and ReUAct datasets demonstrate that the DoT prompting technique significantly outperforms standard prompting, reducing hallucinations and enhancing overall performance. Code and data at *https* : *//github.com/shroglck/llm_hallucination*

1 Introduction

Automatic understanding of human activities in videos remains a challenging problem with significant real-world applications in fields such as healthcare, security, robotics, and elderly care. While recent advancements have been made in recognizing intentional human actions in videos (Kong and Fu, 2022), the recognition and understanding of unintentional activities are equally crucial (Epstein et al., 2020). Beyond mere recognition, understanding the reasoning behind these unintentional actions—specifically, identifying the point of failure—can help in mitigating or correcting mistakes. In this work, we focus on the task of understanding unintentional activities in videos.

Multimodal foundation models have demonstrated impressive zero-shot generalization across various tasks and domains (Zhu et al., 2023; Li et al., 2023a; Zhang et al., 2023a; Li et al., 2023b). In this work, we investigate the reasoning capabilities of Large Multimodal Models (LMMs) concerning action intentionality. Our analysis reveals that conventional prompting approaches often lead to hallucinations and struggle to accurately reason through transitions from intentional to unintentional actions. These models frequently produce generic explanations that fail to fully leverage the available visual context. Although chain of thought prompting (Wei et al., 2022b) offers a structured approach for generating specific explanations, it too suffers from hallucinations when applied to the reasoning of unintentional actions.

To address these challenges, we propose a multistep solution grounded in two key observations: (1) allowing the model to hallucinate multiple responses can sometimes generate correct answers, and (2) framing the task as a multiple-choice problem helps guide the model toward the correct reasoning. Our method, Dream of Thoughts (DoT) prompting, capitalizes on the model's hallucinations by treating them as multiple choices, thereby enabling the model to navigate through these options to arrive at more accurate conclusions.

We conduct experiments on three datasets: OOPs (Epstein et al., 2020), UCF-Crimes (Sultani et al., 2018), and ReUAct. The OOPs dataset focuses on unintentional activities in daily life, while UCF-Crimes highlights anomalous events. To complement these, we introduce ReUAct, a new dataset that captures unintentional activities while minimizing overlap with pretraining datasets. Our extensive evaluations demonstrate the effectiveness of DoT prompting in improving reasoning over unintentional actions. We make the following contributions in this work,

- We introduce a novel problem focused on reasoning about the transition of human activities from intentional to unintentional.

- We evaluate the capability of existing Large Multimodal Models (LMMs) and prompting techniques for this task, and propose a novel reasoning mechanism, Dream of Thoughts (DoT), which outperforms current methods.

- We present ReUAct, a new dataset designed specifically to study the reasoning behind unintentional activities.

- We propose three different evaluation protocols, rm_{MCQ}, rm_{LLM}, and rm_{FIB}, for response matching (rm) which quantifies the reasoning capability of models for this task.

2 Related works

Large generative models: Large language models (LLMs) such as GPT-3 (Brown et al., 2020), LLaMA (Touvron et al., 2023), ChatGPT (OpenAI, 2023), and BARD (Google, 2023) have recently achieved significant advances, excelling in task generalization. Building on this success, Large Multimodal Models (LMMs) have emerged to tackle vision tasks. Notable examples include MiniGPT (Zhu et al., 2023), Open Flamingo (Alayrac et al., 2022), BLiPv2 (Li et al., 2023a), and LLaVA (Liu et al., 2023a) for image-based tasks, as well as Video LLaMA (Zhang et al., 2023a), Video Chat (Maaz et al., 2023), VILA (Lin et al., 2023b), Video-LLaVA (Lin et al., 2023a), and Video Chat-GPT (Li et al., 2023b) for video-based tasks. In our study, we use these LMMs as baselines.

Prompting techniques: Advancements such as Chain of Thought (CoT) prompting (Wei et al., 2022a), Automatic Chain of Thought (Zhang et al., 2022), and Self-Consistent Chain of Thought (Wang et al., 2022) have significantly improved LLMs' zero-shot performance. Multimodal Chain of Thought (Zhang et al., 2023c) extended this approach to incorporate both textual and visual data, while Wang et al. (Wang et al., 2022) refined CoT with self-consistency. Additional developments include the Tree of Thought (Yao et al., 2023b; Long, 2023) and the Graph of Thought (Liu et al., 2023c), which expanded on CoT concepts. Few-shot learning approaches, which incorporate examples, have also enhanced LLM performance (Touvron et al., 2023; Brown et al., 2020), with further improvements by (Liu et al., 2021; Lewis et al., 2020; Paranjape et al., 2023; Zhou et al., 2022). In our work, we analyze and compare LMM reasoning using these techniques alongside our proposed method.

Reasoning abilities of LLM's: (Webb et al., 2023) demonstrated that models like GPT-4 exhibit significant analogical reasoning abilities, while (Liu et al., 2023b) pointed out their limitations when dealing with out-of-distribution data and complex tasks. (Małkiński and Mańdziuk, 2023) further analyzed deep models' analytical reasoning on Raven's Progressive Matrices (Webb et al., 2023). In the Visual Question Answering (VQA) domain, notable advancements have been made by studies such as (Zhang et al., 2023b), (Marino et al., 2021), (Kim et al., 2018), and (Anderson et al., 2018), which have improved VQA methodologies. Additionally, works like (Xue et al., 2023), (Hafner et al., 2019), (Finn and Levine, 2017), (Chang et al., 2016), (Burda et al., 2018), (Babaeizadeh et al., 2021), and (Agrawal et al., 2016) have been instrumental in enhancing deep models' understanding of dynamic visual content. Furthermore, studies such as (Bhattacharyya et al., 2023), (Wu et al., 2021), (Gao et al., 2023), and (Wu et al., 2020) have explored object reasoning in videos through grounding. To the best of our knowledge, no prior work has addressed LMMs' ability to reason about unintentional activities in videos.

Hallucination in LLM's: Hallucination in foundational models refers to the generation of inconsistent or fabricated responses. (McKenna et al., 2023) explored the underlying causes of hallucinations in LLMs, while (Yao et al., 2023a) drew parallels between hallucinations and adversarial examples. (Wang et al., 2023) extended these findings to large vision models (LVMs). To tackle hallucination issues, approaches like self-checking and self-verification were introduced by (Dhuliawala et al., 2023) and (Manakul et al., 2023), aiming to ensure more consistent outputs. In this work, we take a different approach by leveraging hallucinations to enhance the model's reasoning capability through multi-step navigation.

3 Method

Problem statement Our focus is on understanding the transition from intentional to unintentional activities in videos within a zero-shot setting. Given a model $p()$ that accepts a prompt $\mathcal{P}$ and a video $\mathbf{V}$ with n frames as input, the goal is to determine the reasoning $\mathbf{R}$ behind the transition of the activity from intentional to unintentional within the video.
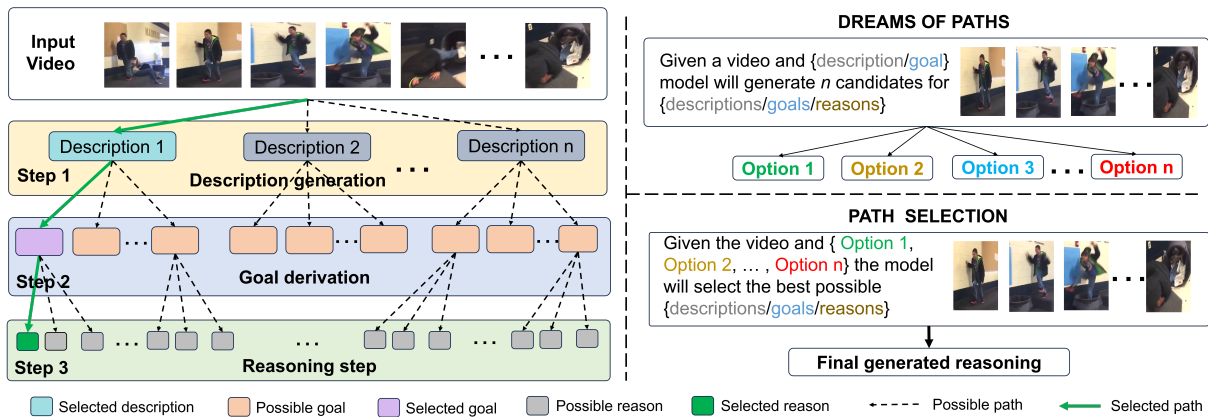
Figure 1: *Overview of the proposed Dream of Thoughts framework:* The left figure shows an overview of the three-step process with all the possible paths generated by the Large Video Language Model using the video and provided prompts. The right figure describes the Dream of Paths mechanism for generating thoughts to cover the most probable options and the Path Selection mechanism for navigating through the best possible options.

3.1 Background and motivation

Our preliminary experiments reveal that Large Video Language Models encounter specific challenges related to hallucinations and their limited ability to infer relationships between events, negatively impacting inference and causal understanding. In our investigation of these issues, we observe that multiple trials often yield accurate responses, with approximately one correct answer emerging from several attempts. Moreover, (Newell et al., 1959, 1972) illustrate that humans interpret problem-solving in a combinatorial fashion, employing heuristics to choose among various possibilities. For humans, prior experiences inform problem-solving strategies and plans. Inspired by this, we propose a multi-step prompting strategy that navigates through the hallucinated responses to enhance reasoning.

3.2 Proposed approach

We introduce the Dream of Thought (DoT) prompting technique to enhance the model's ability to generate accurate responses. This multi-step process consists of three steps designed to obtain essential cues for reasoning. Our primary objective is to understand why a specific activity is perceived as abnormal. This requires the reasoning agent to identify the intended goal of the activity and assess how it deviates from that goal. Specifically, we first obtain a description of the video, using it as a cue to generate the goal of the intentional activity, and then reason why the intentional activity is failing. An overview of the proposed approach is illustrated in Figure 1.

At each step, the Dream of Thought (DoT) process generates a range of possible answers, referred to as Dreams of Paths, in response to a given question. We then implement a Multiple Choice Question (MCQ)-style prompt for effective selection of the most appropriate response (Path Selection) tailored to the specific video. This strategy leverages the model's generative capability to offer diverse options, with the MCQ prompt serving as a filter to identify the most suitable output. While a similar approach has been explored in the Tree of Thoughts (ToT) mechanism (Yao et al., 2023b), there are key differences: 1) ToT relies on a scoring mechanism to select the best option at each step, whereas we frame this as an MCQ for the model itself; and 2) our proposed DoT utilizes cues from previous steps as context for subsequent steps, while ToT treats each step as a partial path without this contextual connection.

The Dream of Thought (DoT) framework comprises three main steps: 1) generating a description, 2) deriving the goal, and 3) reasoning. These steps leverage Dreams of Paths (DoP) and Path Selection. We will first describe the concepts of Dreams of Paths and Path Selection, followed by a detailed explanation of the three steps involved in the DoT prompting process.

Dream of Paths: At each step, we generate n possible options as a solution to the task in corresponding step. The model $p()$ to generate n candidate solutions $x_i \sim p(x_i|V, \dots)$.

Path selection: After obtaining n possible solutions to our problem, we then propose the task as a MCQ form problem where the model has

to select one out of n possible solutions: $x \sim p(x|x_1, \ldots, x_i, P_s, V)$ using a prompt P_s, *"The list of possible descriptions/goals/reasons for the video are given as (descriptions/goals/reasons). Select the most appropriate descriptions/goals/reasons."*

Generating description ($\mathcal{D}$): In the first step, we generate n concise summaries of the video content using a prompt: $d_i \sim p(d_i|P_d, V)$, where prompt P_d is *"Summarize the video action and infer the list of objects exhaustively, from the relevant visual context to the activity occurring in the video."*. Following this, we engage in the Path Selection step to derive the most accurate description of the video: $d \sim p(d|d_1, d_2, \ldots, d_n, V, P_s)$.

Goal derivation ($\mathcal{G}$): Using the summary, we derive n possible intended activity to be executed within the context of this video using a prompt: $g_i \sim p(g_i|d, V, P_g)$, where prompt P_g is given as *"If the summary of the given video is <video summary>, logically infer the most probable intention of the actions being attempted in this video."*. We then perform the Path Selection step to obtain the best possible description for the video: $g \sim p(g|g_1, g_2, g_n, P_s, V, d)$.

Reasoning step ($\mathcal{R}$): Utilizing the information pertaining to the intended activity, we generate a set of n probable factors that could have potentially hindered the successful completion of the aforementioned task: $r_i \sim p(r_i|V, g, P_r)$, using a prompt P_r, *"The goal of the intended activity taking place in the given video is described as: (goal), provide a visual description of the event that leads to the failure to perform the activity with the greatest probability."* This step is again followed by the Path Selection step to obtain the best possible description for the video$r \sim p(r|r_1, r_2, r_n, P_r, V, g)$.

3.3 Evaluation and metrics

We compare the model's responses with the ground truth reasons at both high and low levels of context. For high-level context analysis, we aim to match the underlying reasons provided by the model with the ground truth reasoning, introducing the rm_{LLM} metric for this purpose. In contrast, for low-level contextual analysis, we measure how accurately the model can predict specific attributes of the reason, such as the subject, verb, and object. We propose two metrics for this assessment: rm_{MCQ} and rm_{FIB}. By leveraging keyword-based metrics, we can more precisely evaluate the presence of hallucinations in these models. Specifically, the

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Algorithm 1 Dream of Thoughts (DoT)

Input: Model $\mathcal{M}$, video V_i
Output: Reasoning R
  Input: Model $\mathcal{M}$, video V_i
  $y \leftarrow 1$ Output: $reason$
  $P \leftarrow [P_d, P_g, P_r]$ ▷ Define prompts for reasoning
  $c = []$ ▷ Initialize empty list c for storing context
  $n = N$ ▷ Set n to number of options to be generated
  $P_s = SelectionPriompt$ ▷ Set the selection prompt
  for j in P **do**
    $c_i = []$ ▷ Initialize empty list c_i
    for $i = 1$ **to** n **do**
      $c_i \mathrel{+}= model(c \mid P_j, V, c)$ ▷ Update c_i with model output
    end for
    $c \mathrel{+}= model(c \mid c_i, c, V, P_s)$ ▷ Update c with model output
  end for
  $R = c[-1]$ ▷ Set reason to the last element of c

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absence of keywords suggests potential hallucinations, where keywords may have been replaced by synonyms or replaced with hallucinatory details not originally present.

1) **Low level context evaluation**: The ground truth encompasses subject, object, and verb components extracted from the ground truth, denoted as s_i for the ith video. Our evaluation revolves around the identification of these "keywords" within the predicted responses. This evaluation is applied when the reasoning task is framed as either a multiple-choice question (MCQ) task, or a fill-in-the-blanks task. We experimented with existing metrics for generated text evaluation such as BLEU and Sacre BLEU, but these metrics were unable to match the responses providing most of the scores close to 0 therefore we do not use these metrics.

1.1) *MCQ evaluation:* For MCQ style task, since we provide the ground truth option as one of the options and rest of the options are unrelated, the presence of keywords in the response provides a reasonable estimate of how correct the answer is and also allows us to judge the accuracy of the output. The rm_{MCQ} accuracy is obtained as,

$$rm_{MCQ} = \Sigma_{i=1}^{N} \mathbf{1}[s_i \in pred_i] \tag{1}$$

where $pred_i$ is the prediction given by the model for the ith video in the dataset. Here N is the total number of samples and $pred_i$ is the prediction provided by the model for the i_{th} video.

1.2) *Fill-in-blank evaluation:* In FIB style task since we are removing one of the possible keywords which has to be completed by the model we evaluate the number for keywords model is able to output correctly. We remove s_i from the ground

Models	MCQ				FIB			
	w goal		w/o goal		w goal		w/o goal	
	rm_{MCQ}	rm_{LLM}	rm_{MCQ}	rm_{LLM}	rm_{FIB}	rm_{LLM}	rm_{FIB}	rm_{LLM}
Video ChatGPT	0.303	0.667	0.240	0.457	0.352	0.648	0.222	0.519
Video LLaMA	0.105	0.092	0.099	0.054	0.383	0.139	0.167	0.206
Video Chat	0.315	0.204	0.278	0.067	0.337	0.226	0.215	0.214
Video LLaMAv2	0.134	0.072	0.040	0.067	0.184	0.059	0.293	0.214

Table 1: ***Reasoning capability of existing models:*** Performance evaluation of existing models on multiple-choice questions (MCQ) and fill-in-the-blank (FIB) style prompting. We analyze both scenarios, prompts with and without goals. MCQ setup consist of four questions, 1 ground truth, 2 random and '*None of the above*'.
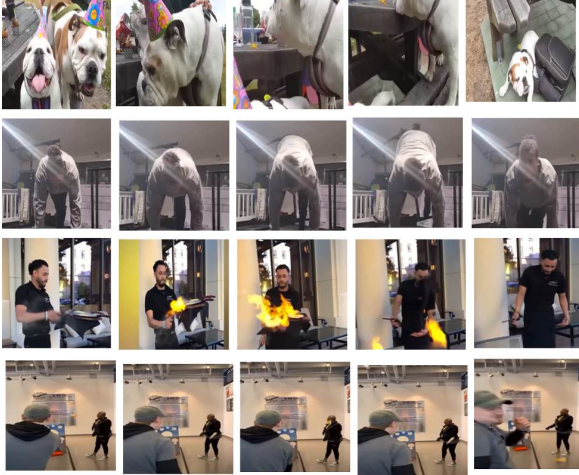

Figure 2: Sample vidoes from the ReUAct dataset. Each row features a distinct video. In the first row, the dog falls off the bench. In the second row, the person hits a machine while trying to handstand. In the third row, the person fumbles flaming dishes. In the last row, a person accidentally hits another person with a flying plane.

truth reason gt_i.

$$rm_{FIB} = \Sigma_{i=1}^N \Sigma_{x_j \in s_i} \frac{\mathbf{1}[x_j \in pred_i]}{len(s_i)}, \quad (2)$$

Here N is the total number of samples, $pred_i$ is the predicted made by the model for the i_{th} video. 2) *Reasoning evaluation:* Finally, we evaluate the response provided by the models and match it with the ground truth answer. We make use of GPT-3.5 for matching the generated and ground truth reason. This evaluation allows us to compare whether the output contains the event which occurs in the ground truth reason. We evaluate the same video five times and report the average score of each video as the rm_{LLM} and the standard deviation of scores per question as std.

4 Experiments

Datasets We performed our experiments on three different datasets, OOPs (Epstein et al., 2020),

UCF-Crimes (Sultani et al., 2018) and ReUAct. **OOPs:** We conduct detailed experimental analysis using the validation subset of the OOPs dataset. This subset comprises 3,500 YouTube videos, each portraying a variety of failures in diverse real-world scenarios. Along with this, the OOPs dataset also contains natural language descriptions for each video. These descriptions provide insights into the original intentions behind the videos and the circumstances leading to the deviation from planned actions. **UCF-Crimes** Further, we also conduct experiments on UCF-Crimes dataset. It consists of long and untrimmed real-world surveillance videos, with 13 realistic anomalies such as fighting, road accident, burglary, robbery, etc. We use the validation set of this dataset to evaluate our approach, where we select only anomalous videos. These videos have length ranging from 1-3 minutes and there are a total of 65 videos in this evaluation set. We provide natural language descriptions for the crime occurring in the videos from this new test set to evaluate our approach. **ReUAct**: We also release a new dataset of recent YouTube videos to avoid potential data leakage into the training datasets for Large Multimodal models. This dataset consists of 100 videos featuring actions failing for various reasons, similar to the OOPs dataset.

Baselines and models For the evaluation and benchmark, we utilize the officially released versions of several state-of-the-art models, namely Video ChatGPT (Maaz et al., 2023), Video LLaMA (Zhang et al., 2023a), Video Chat (Li et al., 2023b), Video LLaVA (Lin et al., 2023a), VILA (Lin et al., 2023b) and Video LLaMAv2 (Zhang et al., 2023a). Along with these video-based models, we also use image based model, Open Flamingo (Alayrac et al., 2022). These models serve as comprehensive baselines in our analysis. Further, we also evaluate different prompting strategies including standard prompting, and the proposed DoT prompt. Each of these models is built upon the LLaMA-7b billion

language model, endowing them with substantial capabilities in text generation from video inputs.

4.1 Quantitative results

We first analyze the reasoning capability of existing LMMs for explaining reasoning behind unintentional activities in videos. Here we explore two different prompting setups, 1) multiple choice questions (MCQs), and 2) fill-in-the-blanks. In MCQ style prompting with n = 3 options (more details in supplementary), we presented several options along with ground truth and prompted the model to select the correct reasoning for the failure. This is evaluated using rm_{MCQ} and rm_{LLM} metrics. In the second setup, we use the ground truth reasoning and randomly remove subject, object or verbs from the sentence and prompt the model to fill in the missing words. This is evaluated using rm_{FIB} and rm_{LLM} metrics.

The performance of studied models for MCQ and FIB style prompting is shown in Table 1. For both, we experimented with two variations, one where the goal is also provided along with the prompt and the other where goal is not provided. Video ChatGPT shows consistently better performance on both FIB and MCQ prompts for all three metrics with and without goal. Video LLaMA and LLaMAv2 show significantly worse performance on MCQ as compared to FIB-style prompts on rm_{MCQ}, rm_{FIB} and rm_{LLM}. Video Chat shows similar performance on rm_{MCQ} and rm_{FIB} but rm_{LLM} for FIB is higher in non-goal setting and similar in with goal setting.

Next, we evaluate the existing and proposed methods for generating the complete reasoning. We evaluate DoT prompting for Video ChatGPT Video Chat, VILA and Video LLaVA in our preliminary experiments. This is evaluated using rm_{LLM} metric along with standard deviation in responses std, which attempts to measure degree of hallucinations in the response.

The evaluation of all the models with all three datasets is shown in Table 2. We can observe that the proposed DoT prompting demonstrate benefits over existing methods surpassing both the standard prompts. DoT outperforms Basic prompts by ∼ 4-10% Furthermore, VILA outperforms rest of the models when subjected to basic prompts. Similar results can be observed for UCF-Crimes dataset and ReUAct Dataset.

Analyzing hallucinations: We provide insights into the standard deviation of scores across individual questions. High standard deviation implies inconsistent answers and substantial model hallucinations. Conversely, a low standard deviation, coupled with low accuracy, suggests consistent but incorrect responses, while a low standard deviation with high accuracy indicates consistent and correct answers. From Table 2 we can observe that DoT has lower std score than basic prompts by ∼ 0.02 in most cases apart from VILA. Additionally, in Figure 4 we can see that the outputs obtained from DoT prompt display a consistently higher cosine similarity score to ground truth reason as compared to the output obtained from standard prompts (Details in supplementary).

Human Evaluation: We also conduct human evaluations of responses generated by benchmarked LMMs. We randomly sampled 100 videos for OOPs and 50 videos each for ReUAct and UCF-Crimes datasets, and compared the models' outputs with ground truth. As shown in Table 2, the results indicate a trend similar to rm_{LLM}, suggesting that LLM-based evaluation effectively measures the similarity between ground truth reasons and model outputs.

4.2 Qualitative Results

We present qualitative results on the OOPs and UCF-Crimes dataset in Figure 3. We can observe that DoT prompting is generating better reasoning for action failures as well reasoning behind the the activity being anomalous in videos, compared to Standard and CoT prompting. The DoT method is better aligned with ground truth reasoning, showcasing its capability across diverse activities such as typing, shooting an air gun. These activities highlight different success scenarios: ongoing success in working, and instant success in air gun shooting. It also demonstrates its effectiveness to identify a wide range of crimes like arson and vandalism showcasing its generalizability.

4.3 Ablation studies

We conduct ablation studies to assess the impact of prompt variations on both accuracy and the presence of hallucinations these ablations studies aid in evaluating the efficacy of each individual step within our proposed DoT prompting methodology **Effect of number of options:** In MCQ-style question answering, we explore how varying the number of options in MCQs impacts performance. In Figure 5, we initially observe a gain of 3% and 6%
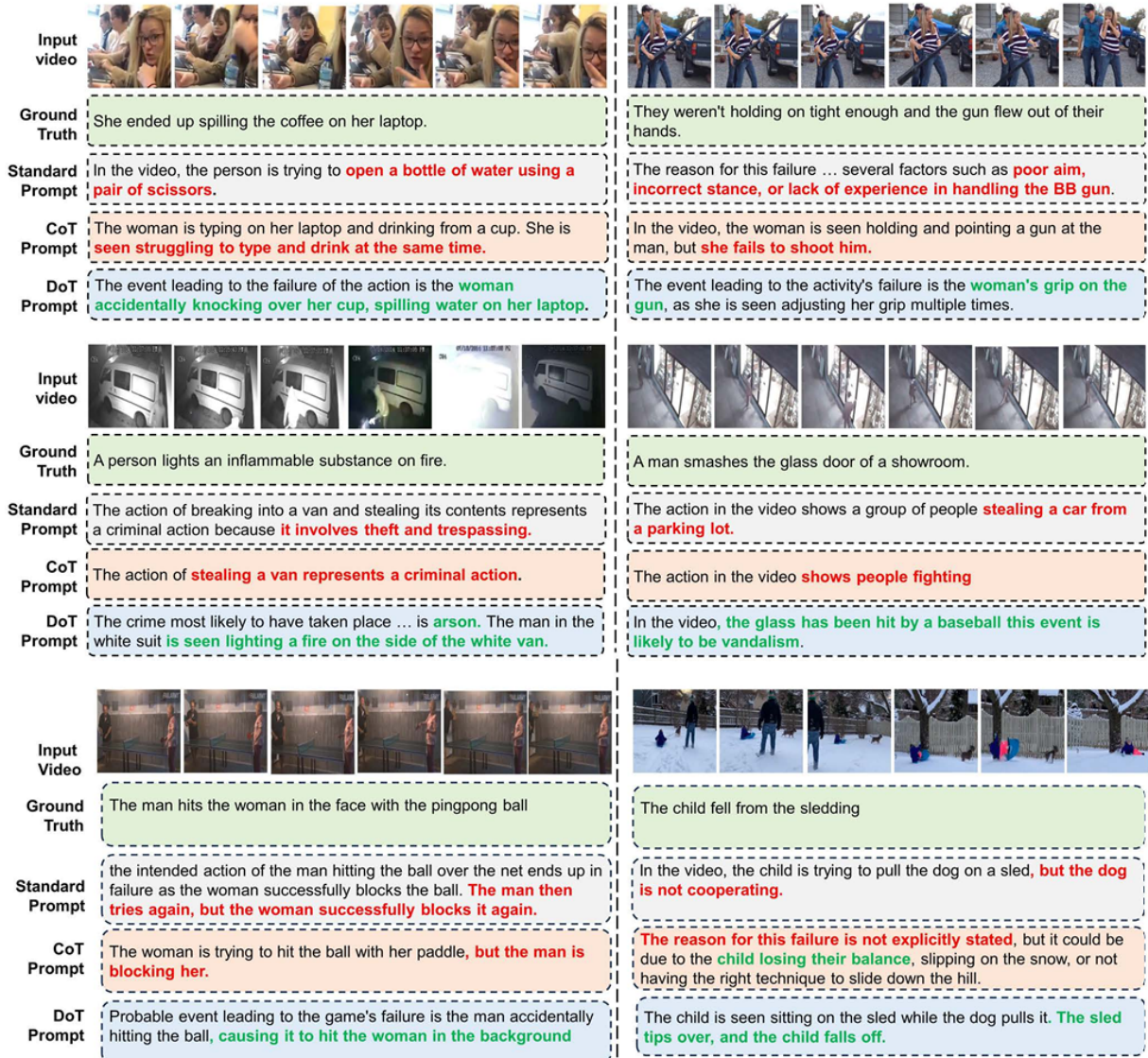
Figure 3: *Qualitative evaluations:* We show some samples for qualitative analysis of the proposed DoT prompting compared with CoT and standard prompting. First row illustrates examples from OOPs dataset and the second row refers to examples sampled from UCF-Crimes dataset and the third row from the ReUAct dataset.

Dataset	OOPs			UCF-Crimes			ReUAct		
Model	rm_{LLM}	std	H	rm_{LLM}	std	H	rm_{LLM}	std	H
Open Flamingo	0.154	0.128	0.160	0.035	0.047	0.000	0.234	0.070	0.053
Video LLaMA	0.026	0.048	0.014	0.075	0.072	0.011	0.028	0.069	0.009
Video Chat	0.064	0.156	0.009	0.082	0.143	0.007	0.033	0.024	0.007
Video LLaMA2	0.053	0.089	0.011	0.081	0.089	0.013	0.024	0.071	0.011
Video ChatGPT	0.242	0.217	0.186	0.247	0.171	0.182	0.173	0.141	0.200
Video LLaVA	0.359	0.187	0.413	0.254	0.144	0.205	0.292	0.149	0.233
VILA	0.451	0.201	0.495	0.260	0.136	0.395	0.327	0.167	0.268
DoT(V-GPT)	0.279	0.199	0.278	0.291	0.160	0.240	0.179	0.161	0.240
DoT(V-Chat)	0.069	0.071	0.070	0.012	0.071	0.005	0.037	0.021	0.006
DoT(V-LLaVA)	0.446	0.178	0.470	0.291	0.073	0.237	0.367	0.172	0.344
DoT(VILA)	0.520	0.157	0.560	0.334	0.183	0.437	0.365	0.215	0.381

Table 2: *Performance evaluation:* A comparison of existing methods with proposed DoT prompting on OOPs ReUAct and UCF-Crimes dataset. We show both rm_{LLM} and standard deviation (std) across five trials. DoT refers to the proposed prompting strategy. H refers to human evaluation.
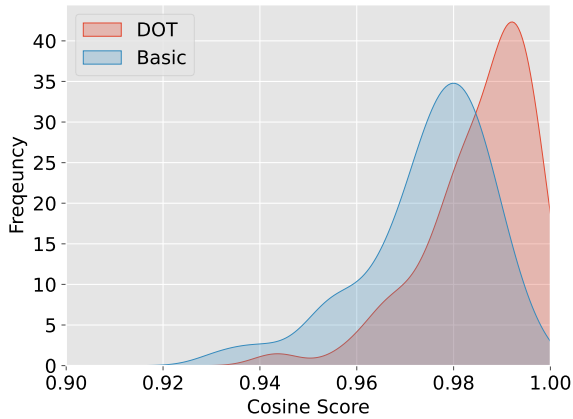
Figure 4: Distribution of cosine similarity between ground-truth and the DoT as well as basic prompt.
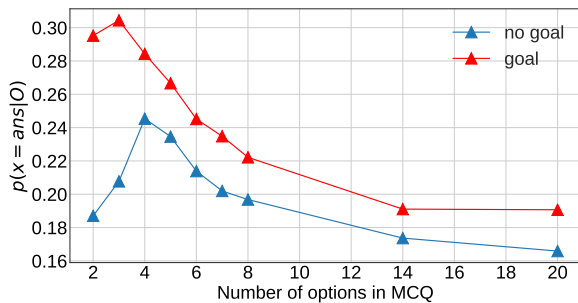

Figure 5: ***Effect of number of options:*** Variation of $p(x = ans|O)$ on reasoning task proposed as MCQ style query, with varying number of present in a MCQ question, where $p(x = ans|O) = 1 \, if \, frm_{mcq} >= 0.8$ else $p(x = ans|O) = 0$. Here O refers to the options presented in the MCQ.
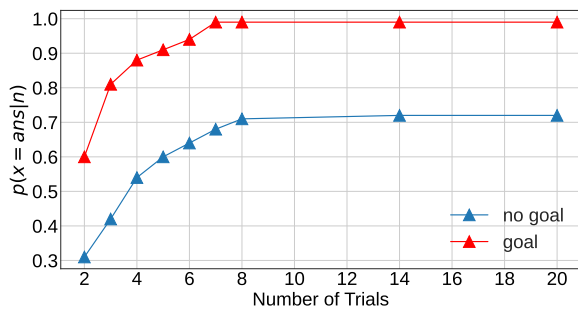

Figure 6: ***Analyzing number of trials:*** Variation of $p(ans \in x|n)$ on reasoning task proposed as MCQ style query, with n is the number of times prompt has been evaluated using LMM and x is set of n outputs obtained using LMM.

for with and without goal settings, which is followed by a reduction of 12% in rm_{MCQ}, when the number of options is increased in both scenarios. We hypothesize that the first increment is because more tries allow the model to generate better op-

	with goal		w/o goal	
Model	rm_{LLM}	std	rm_{LLM}	std
Video ChatGPT	0.621	0.213	0.242	0.217
Video LLaMA	0.337	0.261	0.026	0.048
Video Chat	0.205	0.301	0.064	0.156
Video LLaMA2	0.033	0.032	0.053	0.089

Table 3: ***Effect of goal:*** Performance comparison of models on reasoning with provided goals.
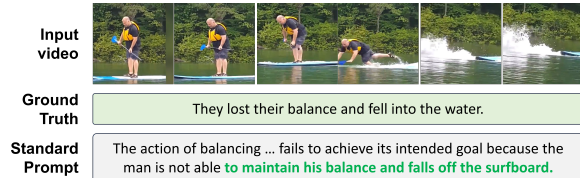

Figure 7: ***Role of visual information:*** We observe some interesting scenarios where the model using a standard prompt with goal of the video provided is able to infer the correct reasoning without any video frames.

tions as shown in Figure 6. The decrease afterward is likely due to the broadening of the model's search space, resulting in more inaccuracies. The score becomes almost constant after 14 options for both cases.

Effect of goal: Humans excel at understanding actions with context. In this experiment, we introduce the goal of the attempted action as added context. For this, we construct the prompt as Prompt: *"If the goal of the activity occurring in the video is (goal). Explain the reason behind the failure to achieve the desired goal."*.Analysis of the results, as presented in Table 1 and Table 3, reveals that the inclusion of goal enhances the reasoning capabilities of these models. We can see that the presence of goal increases the rm_{LLM} by 0.4 in Video Chat-GPT and by $0.2 \sim 0.3$ for Video Chat and Video LLaMA models, whereas Video LLaMAv2 seems to perform worse in both conditions.

Effect of Dream of Paths: We evaluate the Dream of Paths by modifying the prompt to exclude the Dream of Paths step for both descriptions and goals. Results in Table 4, reveal that removing this (DoT(w/o des)) leads to a significant decline in performance. This decrease can be attributed to the reliance on inaccurate descriptions for subsequent steps, resulting in incorrect reasons. Furthermore, generating a single option for both description and goal (DoT(w/o goal des)) shows marginally better performance compared to DoT(w/o des), but less than DoT method.

Effect of Path Selection We compared our Path Selection procedure used in against the DoT(rm_{FIB})

Model	rm_{LLM}	std
CoT	0.237	0.182
DoT(w/o des)	0.180	0.153
DoT(w/o goal,des)	0.221	0.182
DoT(rm_{FIB})	0.260	0.183
DoT	0.279	0.199

Table 4: *Ablation Analysis of the DoT Prompt*. DOT(w/o des) refers to the case when we directly obtain description. Similarly, in DoT(w/o goal, des) we directly obtain goal and description. In DoT(rm_{FIB}) the path selection is performed using rm_{FIB}.
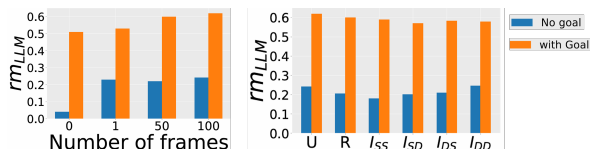

Figure 8: *(Left)* Effect of varying the number of sampled frames on rm_{LLM} for reasoning task. *(Right)* We show effect of various frame sampling techniques in videos: U(uniform sampling), R(random sampling), I_{SS} (sparse sampling from both intentional and unintentional parts), I_{SD} (sparse from intentional, dense from unintentional), I_{DS} (dense from intentional, sparse from unintentional), and I_{DD} (dense sampling from both intentional and unintentional parts)

approach, where we select the option with the highest rm_{FIB} at each stage to match relevant objects. Our results, as detailed in Table 4, show that using the FIB method, while resulting in a lower std, achieves a slightly lower performance compared to the base DoT by 2%.

4.4 Analysis

Number of video frames: We conducted an analysis on the effect of the number of frames. We vary the number of frames, from 0 to 100 frames. Our observations, as depicted in Figure 8, reveal that the model's performance remains stable concerning the number of frames but experiences a substantial drop in 0 frame setting. Interestingly, for some scenarios (Figure 7) just the goal of the activity allows the model to achieve significantly high rm_{LLM} using only the goal as information about the video, which shows that it utilizes textual conditioning more efficiently than visual modality.

4.5 Sampling Strategy

We explore variations in the frame sampling strategy, ranging from uniform and random sampling to importance sampling. Importance sampling involves selectively sampling frames sparsely or densely from the intentional and unintentional seg-

ments of the video. To execute importance sampling, we utilize timestamps provided for intentional and unintentional parts of the video with the OOPs dataset, sampling varying numbers of frames from the intentional and unintentional parts. Our findings, presented in Figure 8, show that sampling strategies do not significantly affect the reasoning capabilities of Video ChatGPT.

5 Conclusion

In this work, we present a novel task regarding understanding of unintentional activities in videos where we formalize it as a zero shot reasoning task. We first analyze the reasoning capabilities of existing LMM models and prompting techniques and then also propose a novel DoT prompting technique which navigates through hallucinations introduced by LLM's to obtain the reasoning. We propose different metrics to quantify the models performance and also analyze hallucinations of the responses. We further demonstrate that the proposed method outperforms existing prompting techniques.

6 Guidelines

6.1 Limitations

In this work we explore reasoning where the event that causes the action to fail occurs immediately before the actual failure of the action. We do not consider actions which may cause failure of the action at a later moment in time with long-term reasoning and it will be an interesting direction to explore.

6.2 Risks

This research may pose some risk for privacy if it is used along with a surveillance system.

6.3 Licenses

OOPs dataset - Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International License. Video ChatGPT- Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International License. LLaMA- LLAMA community license agreement UCF-Crimes - Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International License. Video LLaVA -Apache 2.0 License. VILA Apache 2.0 License. ReUAct-Creative commons Attribution-NonCommercial-ShareAlike 4.0 International License.

6.4 Computation

All experiments we performed using a single V-100 32 GB GPU with each model taking around 10 hours for evaluation.

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A Appendix

A.1 Cosine similarity

To obtain the cosine similarity score for Figure 4 we prompt the model as the **Prompt:** *"Given the video goal of the activity occurring in the video as <goal> and reason behind its failure as <reason>"* and take the embedding obtained from the encoder of Video-ChatGPT model. For ground truth encoding we replace <reason> with the ground truth reason similarly for DoT and Basic prompt with reasoning obtained from using repsective prompts.

A.2 LLM Evaluation

We use GPT-3.5 for evaluation using LLM. To obtain the score we prompt GPT-3.5 as **Prompt:** *"You are provided with a question,the correct answer and the predicted answer. The question contains information about the task being attempted to be achieved in the video, along with the context about the objects involved in achieving that goal. The correct answer consists of the reasons behind the failure of achieving that objective and information about the objects present during the failure. Your task is to evaluate the correctness of the predicted answer. Here's how you can accomplish the task:// "——" "INSTRUCTIONS: //" "- Focus on the meaningful match of events between the predicted answer and the correct answer.*
" "- Consider synonyms or paraphrases as valid matches.
" "- Evaluate the correctness and alignment of the predicted answer compared to the correct answer. ",

"role": "user",
"content":
"Please evaluate the following video-based question-answer pair:
" f"Question: question
" f"Correct Answer: answer
" f"Predicted Answer: pred
" "Provide your evaluation only as a yes/no and score where the score is an integer value between 0 and 1, with 1 indicating the highest meaningful match. " "Please generate the response in the form of a Python dictionary string with keys 'pred' and 'score', where value of 'pred' is a string of 'yes' or 'no' and value of 'score' is in NUMBER, not STRING."
"DO NOT PROVIDE ANY OTHER OUTPUT TEXT OR EXPLANATION. Only provide the Python dictionary string. " "For example, your response should look like this: 'pred': 'yes', 'score': 0.8." Where the correct reason is the ground truth reason the question is given as ***If the <goal> of the action occurring in the given video infer the reason why the action fails to achieve the intended outcome*** and predicted answer is the answer obtained using the respective prompting technique.

A.3 MCQ Style Prompt

To formulate the MCQ style prompt mentioned in 1 containing n options we first randomly select ground truth reasons behind the failure of actions to obtain n-2 options. In addition to these N-2 options we also provide the ground truth reason for that particular video and None of these option as well. The prompt provided to the model is given as ***The action occurring in the given video fails.You will be given*** $num\_options$ ***describing the reasoning behind the failure. The options for this video are given as*** $options\_list$. where $num\_options$ is the number of options provided in the MCQ style prompt and $options\_list$ refers to the list of options provided to the MCQ style prompt.

A.4 FIB style prompt

To formulate the FIB style prompt used in 1 we first use the ground truth reason behind the failure contain a list of s subjects v verbs and o objects. First we randomly remove s , v and $o's$ and replace it with ___. The sentence obtained after it is ***They _____ the _____ too high and ___ a _____ _____ off.*** Finally we prompt the model with ***Given the following video complete the following sentence such that the sentence describes the reasoning behind failure of the intended action in the video. The sentence to be completed is <sentence>. Note: Your task is to complete the given sentence where the blanks are indicated by _____.***

A.5 UCF-Crimes Dataset Annotation

UCF-Crimes Dataset does not provide natural language descriptions for the reasoning behind the event occurring the video being a crime. We manually annotate each anomalous video in the validation set by providing information about the actor, who commits the crime, the crime committed in the video and the victim of the crime, if applicable in the video for example in Figure 9 in the last row represent examples from UCF-Crimes dataset. From the ground truth annotations we can note

the presence of the actor the crime and victim(if present) in each annotation.

A.6 ReUAct

We propose a dataset ReUAct which consists of 100 videos collected from YouTube featuring unintetional activities. The length of each video collected varies from 3 seconds to 8 seconds. All of these videos were collected and annotated manually by the authors. We collected videos made available on or after November 2023 from Youtube to ensure minimal leakage of videos into datasets used for training Large Multimodal Models. Annotations were made in a manner similar to the OOps dataset and can be seen in **??**.We manually annotate each anomalous video by providing information about the actor, who commits the action, how the action goes wrong.

A.7 Human Evaluation Protocol

We evaluate responses provided by models to the ground truth by comparing the object, actor, intended action and reason behind failure. We give equal importance to all these factors to score the responses.
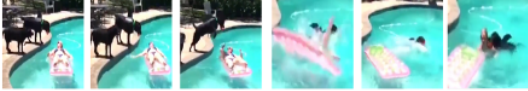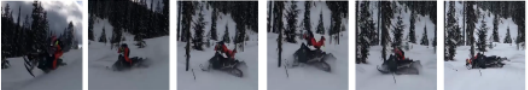
Figure 9: We show some samples for the qualitative results of the proposed DOT prompting compared with COT and standard prompting for UCF-Crimes and OOPs dataset.
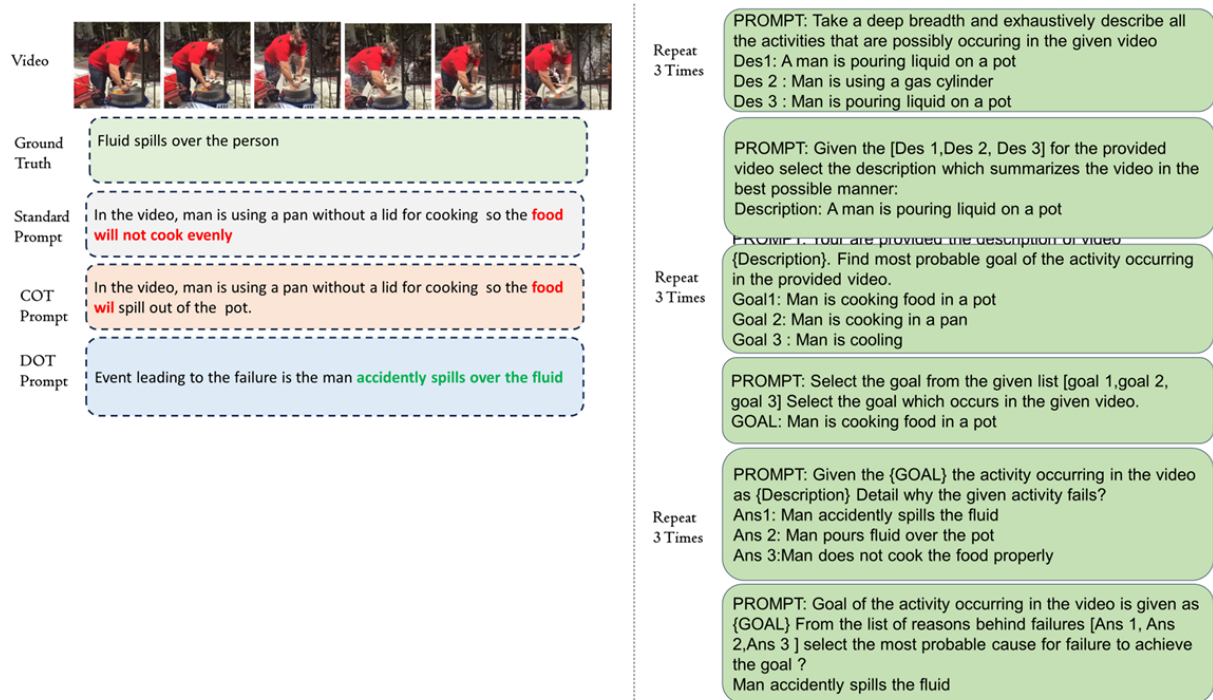
Figure 10 (left column):

Video

Ground Truth: Fluid spills over the person

Standard Prompt: In the video, man is using a pan without a lid for cooking so the **food will not cook evenly**

COT Prompt: In the video, man is using a pan without a lid for cooking so the **food wil spill** out of the pot.

DOT Prompt: Event leading to the failure is the man **accidently spills over the fluid**

Figure 10 (right column):

Repeat 3 Times — PROMPT: Take a deep breadth and exhaustively describe all the activities that are possibly occuring in the given video
Des1: A man is pouring liquid on a pot
Des 2 : Man is using a gas cylinder
Des 3 : Man is pouring liquid on a pot

PROMPT: Given the [Des 1,Des 2, Des 3] for the provided video select the description which summarizes the video in the best possible manner:
Description: A man is pouring liquid on a pot

Repeat 3 Times — PROMPT: Your are provided the description of video {Description}. Find most probable goal of the activity occurring in the provided video.
Goal1: Man is cooking food in a pot
Goal 2: Man is cooking in a pan
Goal 3 : Man is cooling

PROMPT: Select the goal from the given list [goal 1,goal 2, goal 3] Select the goal which occurs in the given video.
GOAL: Man is cooking food in a pot

Repeat 3 Times — PROMPT: Given the {GOAL} the activity occurring in the video as {Description} Detail why the given activity fails?
Ans1: Man accidently spills the fluid
Ans 2: Man pours fluid over the pot
Ans 3:Man does not cook the food properly

PROMPT: Goal of the activity occurring in the video is given as {GOAL} From the list of reasons behind failures [Ans 1, Ans 2,Ans 3] select the most probable cause for failure to achieve the goal ?
Man accidently spills the fluid

Figure 10: We show some samples for the qualitative results of the proposed DOT prompting compared with COT and standard prompting for OOPs dataset with outputs for every step.

Figure 11 (left column):

Video

Ground Truth: Server drops the plates after lighting them on fire

Standard Prompt: The mans attempt to light fire fails because **he is not using proper technique**

COT Prompt: In the video, man is unable to **light fire on the table**.

DOT Prompt: Man drops **fire ball on the ground and it goes out.**

Figure 11 (right column):

Repeat 3 Times — PROMPT: Take a deep breadth and exhaustively describe all the activities that are possibly occuring in the given video
Des1: Man is presenting a fire based demonstration at a restaurant.
Des 2: Man is carrying a plate with fire
Des 3 : Man presenting fire

PROMPT: Given the [Des 1,Des 2, Des 3] for the provided video select the description which summarizes the video in the best possible manner:
Description: Man is presenting a fire based demonstration at a restaurant.

Repeat 3 Times — PROMPT: Your are provided the description of video {Description}. Find most probable goal of the activity occurring in the provided video.
Goal 1 :Man is performing a fire based demonstration
Goal 2: Man is serving fire
Goal 3 : Man is performing fire based demonstration

PROMPT: Select the goal from the given list [goal 1,goal 2, goal 3] Select the goal which occurs in the given video.
GOAL : Man is performing a fire based demonstration to entertain

Repeat 3 Times — PROMPT: Given the {GOAL} the activity occurring in the video as {Description} Detail why the given activity fails?
Ans1: Man drops fire ball on the ground
Ans 2: Man drops plates on the ground
Ans 3: Man drops dishes on the ground

PROMPT: Goal of the activity occurring in the video is given as {GOAL} From the list of reasons behind failures [Ans 1, Ans 2,Ans 3] select the most probable cause for failure to achieve the goal ?
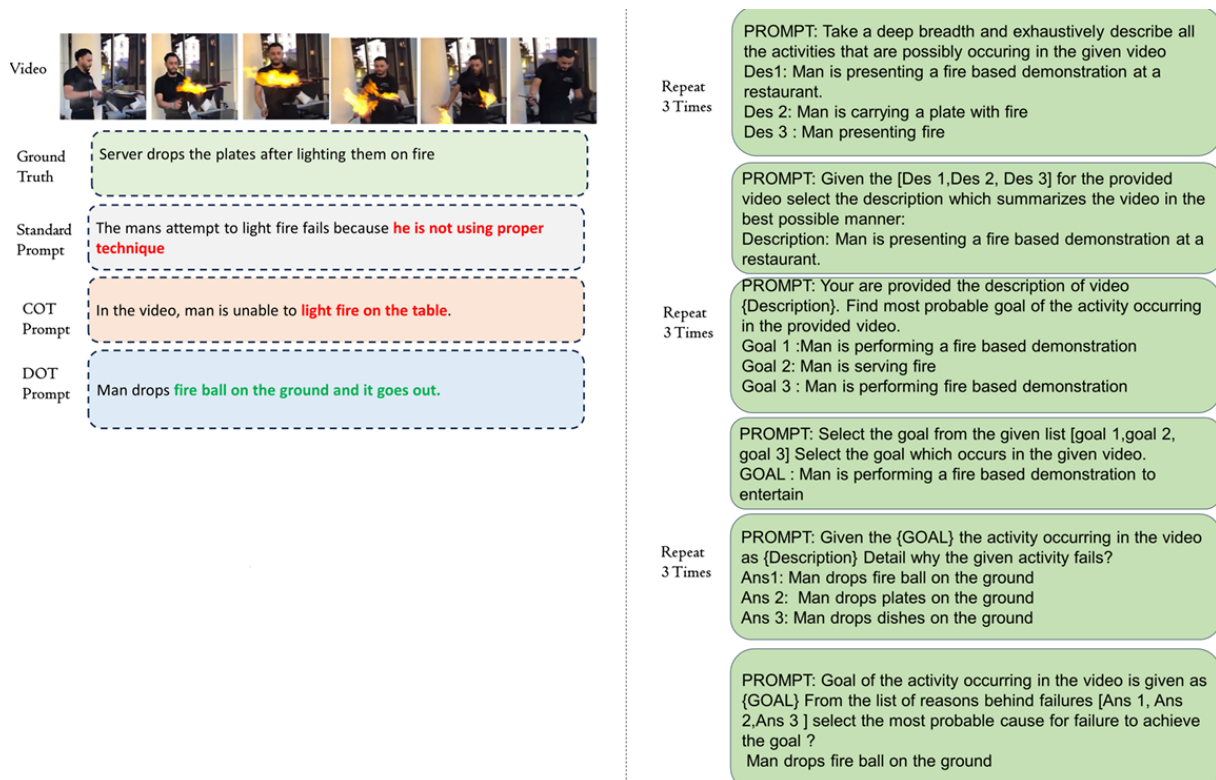Man drops fire ball on the ground

Figure 11: We show some samples for the qualitative results of the proposed DOT prompting compared with COT and standard prompting for OOPs dataset with outputs for every step.