Navigating Connected Memories with a Task-oriented Dialog System

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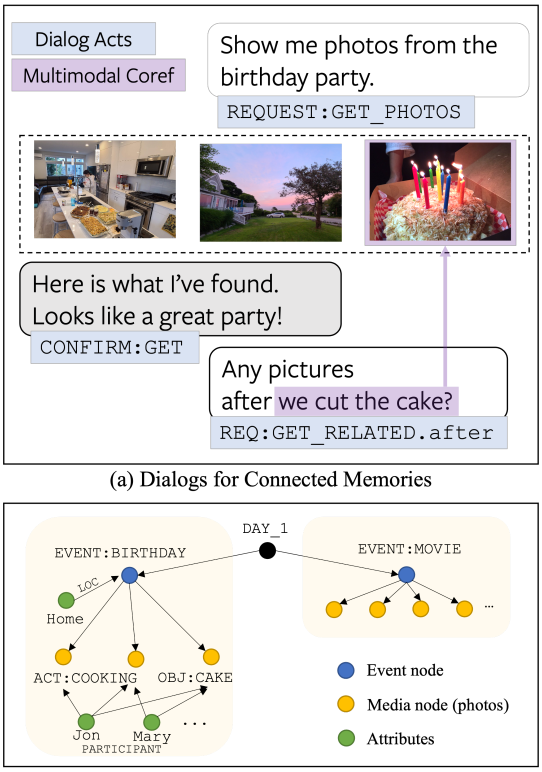
Abstract

Recent years have seen an increasing trend in the volume of personal media captured by users, thanks to the advent of smartphones and smart glasses, resulting in large media collections. Despite conversation being an intuitive human-computer interface, current efforts focus mostly on single-shot natural language based media retrieval to aid users query their media and re-live their memories. This severely limits the search functionality as users can neither ask follow-up queries nor obtain information without first formulating a single-turn query.

In this work, we propose *dialogs for connected memories* as a powerful tool to empower users to search their media collection through a multi-turn, interactive conversation. Towards this, we collect a new task-oriented dialog dataset COMET, which contains $11.5k$ user$\leftrightarrow$assistant dialogs (totalling $103k$ utterances), grounded in simulated personal memory graphs. We employ a resource-efficient, two-phase data collection pipeline that uses: (1) a novel multimodal dialog simulator that generates synthetic dialog flows grounded in memory graphs, and, (2) manual paraphrasing to obtain natural language utterances. We analyze COMET, formulate four main tasks to benchmark meaningful progress, and adopt state-of-the-art language models as strong baselines, in order to highlight the multimodal challenges captured by our dataset. Our code & data will be made publicly available.

1 Introduction

The rise of smartphones and smart glasses has contributed to a surge in the amount of personal media (photos, videos, montages, *etc.*) captured by users on a day-to-day basis in the past decade. For instance, it is estimated that about 1.5 trillion photos would be clicked in the year 2022 (Pantic, 2021). As a result, personal media collections typically grow at an alarming rate, making it cumbersome for users to manually search, retrieve, and re-live their captured memories[1].



(a) Dialogs for Connected Memories

(b) Memory Graph

Figure 1: Illustration of COMET: **CO**nnected **ME**mories with a **T**ask-oriented Dialog. (a) Each dialog turn is fully annotated with dialog acts and multimodal coreference labels, accompanied with photos associated with the request. (b) These media are from the underlying memory graph, a structured collection of personal media.

To alleviate this situation, solutions that perform natural language query-based media retrieval (Tan et al., 2019; Vo et al., 2019; Tellex and Roy, 2009; Barbu et al., 2013; Li et al., 2017; Guo et al., 2018a; Saha et al., 2018) have been proposed. However, such approaches exhibit two drawbacks. First, they are single-shot interactions without any context carry-over, *e.g.*, *Show me some photos from the beach last week.*. This limits the functionality and does not let users ask any follow-up queries like

[1] Memories and media files are used interchangeably.

'Display photos from the first time I was <u>*here*</u>*?'*, since understanding <u>here</u> requires the query history. Second, users cannot seek information without actually formulating the query to retrieve the corresponding memory. For instance, there is no easy query to know the first time a user visited the beach in the memory they are reviewing.

In order to overcome these limitations, we propose *dialogs for connected memories* as a powerful interface where users can interactively query their memory collections. By design, a conversational agent can handle multi-turn interactions enabling several additional queries that require context carryover, *e.g.*, *'When was the first time I was at this beach?'*. Though prior efforts have explored the use of dialogs in media retrieval (Wu et al., 2021; Guo et al., 2018b) in other domains (e.g., fashion), there is no existing work focusing on interactive search and query of personal media collections to the best of our knowledge.

More concretely, we propose COMET, a new multimodal task-oriented dialog dataset aimed at developing conversational assistants that can enable users to interactively search and query their collection of memories. Working with personal media collections presents two main obstacles: (a) There are no readily available public datasets that contain personal media along with associated media attributes that we could leverage, and, (b) Personal memories constitute sensitive information, thus resulting in privacy and safety concerns. To circumvent these roadblocks, we devise a novel memory graph simulator that can leverage publicly available media datasets and help create several synthetic memory collections. We represent these collections as memory graphs to capture useful relationships between the constituent memories, *e.g.*, memories taken at the same place. We then collect $11.5k$ user↔assistant task-oriented dialogs (totalling $103k$ utterances), grounded in $1.1k$ memory graphs. An example dialog is shown in Fig. 1.

Our dataset is challenging as it requires reasoning through both the dialog history and multimodal context (memory graphs) to resolve coreferences, track the dialog state, predict the right API, and generate a meaningful natural language assistant response. As an example, consider the query *'When was the first time I was* <u>*here*</u>*?'*. First, the model needs to resolve <u>here</u> using the dialog history and previously viewed memories. Next, it needs to understand that the query is seeking information about a *connected memory*, and predict the right API `get_time(resolve(`*here*`),` *first time*`)`. Finally, it should produce a response like *'The first time you were here was on August 2, 2019 with Jean'*, potentially including some chit-chat.

To capture these challenges and benchmark progress towards assistants that can interactively handle dialogs for connected memories, we formulate four main tasks: Assistant API Call Prediction, Multimodal Coreference Resolution (MM-Coref), Multimodel Dialog State Tracking (MM-DST), and Response Generation. We train baseline models for these tasks, and discuss future research directions.

2 Related Work

Task-oriented Dialogs: The goal of a task-oriented dialog system is to understand user queries and accomplish a pre-defined set of tasks (*e.g.* booking hotels), which is a popular setting in consumer-facing virtual assistants. Our work addresses similar challenges often found in other task-oriented dialogs, such as natural language understanding (NLU), dialog state tracking (DST) (Henderson et al., 2014), etc. Compared to the conventional task-oriented dialog datasets (*e.g.* MultiWoZ (Budzianowski et al., 2018; Eric et al., 2019; Rastogi et al., 2019)), however, our work involves a unique multimodal setting where dialogs are grounded on a memory graph composed of several media files, introducing novel challenges such as multimodal dialog state tracking and multimodal coreference resolution given personal photo collections.

The most notable modeling approaches for task-oriented dialog systems include casting the DST task as a joint causal language modeling problem (Hosseini-Asl et al., 2020; Peng et al., 2020; Gao et al., 2019), by fine-tuning a large pre-trained transformers such as GPT-2 (Radford et al., 2019). We follow this recent trend and provide baselines by extending it accommodate for the unique multimodal contexts that our dataset brings.

Memory QA: Our work is also similar to the Memory QA tasks (Jiang et al., 2018; Moon et al., 2019), where the main task is to answer user QA queries upon a collection of images, extending the Visual QA tas (Antol et al., 2015) which operates on a single image. However, the existing literature is limited to a simple single-turn QA interaction, and focuses on the identification of an evidential image to answer a question. While our dataset does include QA queries, we extend the problem do-

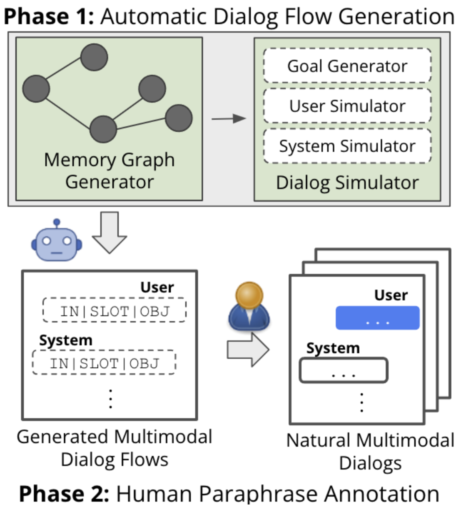


Figure 2: Two-stage pipeline to collect dialogs for COMET. See Sec. 3 for more details.

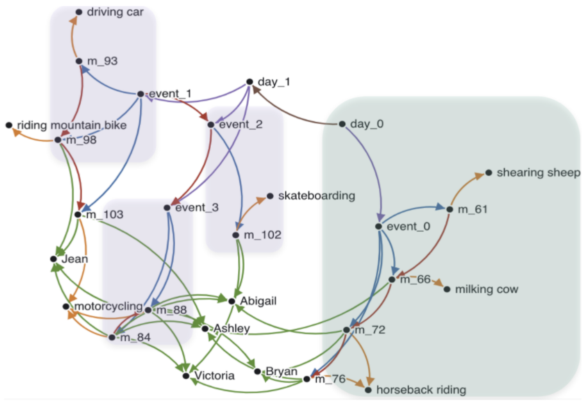


Figure 3: Memory subgraph with constituent memories and their hierarchical relationships. Each memory contains activity (orange), people (green), time, and place (not shown) attributes. Memories are grouped into events (purple box), then days (green box), and finally trips (shown subgraph). Each memory graph contains multiple trips, though only one is shown here for brevity.

main to the conversational settings which support complex scenarios (*e.g.* searching for related memories), allowing for rich multimodal interactions.

3 The COMET Dataset

The aim of COMET is to enable assistant systems that can process interactive queries from users and help navigate their collection of memories through a natural language conversation. Towards this, we collect the COMET dataset using a two-phase approach (shown in Fig. 2): (a) Generating synthetic dialog flows between a user and an assistant that are conditioned on memory graphs, using a novel multimodal dialog simulator (Sec. 3.1), and, (b) Manually paraphrasing the above flows to obtain dialogs with natural language utterances (Sec. 3.2), thus moving closer to real-world application. This approach is resource-efficient as it reduces the annotation overheads when compared to collecting human↔human dialogs, both in terms of cost and time. In what follows, we describe these two phases in detail and analyze our COMET dataset. See the supplementary (Fig. 7) for an example dialog.

3.1 Multimodal Dialog Self-play

We first leverage a multimodal dialog simulator (Sec. 3.1.2) to generate synthetic dialog flows between a user and an assistant. Each of these flows is grounded in a graph connecting the memories of a user from their collection. The memory graphs in our work are simulated by a novel graph simulator (Sec. 3.1.1) and are designed to capture several hierarchical relationships between the user memories.

3.1.1 Memory Graph Simulator

Graphs have been ubiquitously used in various fields to effectively represent a set of entities and relationships between them. Following this trend, we use a graph structure to represent a collection of memories (see Fig. 3 for an example). As mentioned in Sec. 1, to circumvent the lack of readily available datasets for personal photo collections and surrounding privacy issues, we construct a novel graph simulator to synthetically generate memories graphs using public datasets. These memory graphs are then used as an input to the multimodal dialog simulator to generate dialog flows.

Memories and Attributes. Memories constitute the atomic units of the graph simulator, and can cover a wide variety of media including photographs, videos, and user-created montages. We limit the scope of memories to represent static images in this work, although most components of our proposed framework readily extend to the broader definition. As photo collection of individuals is sensitive information, we use publicly available image dataset as a proxy to mitigate the risk. Specifically, we use Creative Commons images from MS COCO (Lin et al., 2014) that contains objects and people in everyday contexts as memories.

We then assign four attributes to each of the images as follows: (a) *Activity*: Each image in MS COCO has 5 associated captions. We use sentence-BERT (Reimers and Gurevych, 2019) to find the closest activity label from the taxonomy of the ActivityNet dataset (Heilbron et al., 2015), using average text-similarity to the captions. To ensure a good representation, we only keep those with at least 20 memories resulting in about 138 labels covering wide variety of activities. (b) *Place:* For each activity, we first manually map it to a place type, which then is randomly mapped to an actual place from a manually curated list. For instance, *playing frisbee → park → Cal Anderson Park, Seattle, USA*. (c) *People:* We use the associated bounding box annotations for MS COCO images and map those labeled as 'person', above a threshold size, to a random name from a curated list of 200 names. (d) *Time* attribute is sampled randomly from a constrained time range, depending on the relationship shared with other memories in the graph.

Hierarchical Relationships. To closely emulate scenarios in a personal photo collection, we devise the following hierarchy of relations amongst the memories: *memories → events → days → trips*. Using heuristic rules, we sample and group memories into events that are then grouped into days, which are finally grouped into trips. These groupings impose constraints on the attributes of the constituent memories, which can be used to generate interesting conversational flows to query connected memories. For instance, memories from the same event need to happen at the same place type, while those in a day need to happen in the same city. Similar restrictions arise for the time attribute as well, which would be used to sample reasonable times for the corresponding memories, *e.g.*, memories from the same event cannot be separated by more than few hours. These hierarchical relationships enable connected queries like *'What did we do after this?'*, *'Show other pictures with Jane on this trip'*, or *'Where did we go the next day?'*.

Memory Graphs. Putting everything together, we construct a memory graph for each collection:

- nodes: memory, event, day, trip, person, activity
- edges: memory attributes, hierarchical relations

Note that each memory graph can contain multiple trips. Fig. 3 illustrates a memory subgraph, visualizing only one trip for brevity. We synthetically generate multiple memory graphs which form the input to the dialog flow simulator.

3.1.2 Multimodal Dialog Simulator

The multimodal dialog simulator takes the generated memory graphs along with the meta information of each node to create user↔assistant dialog flows, following the agenda-based dialog simulator approach (Schatzmann et al., 2007).

Dialog Flow Generation via Self-play. The dialog simulator comprises three main components: the *goal generator*, the *user simulator*, and the *assistant simulator*. The goal generator randomly samples an *agenda* for each dialog, which defines a sequence of high-level *goals* for the scenario (*e.g.*, `SEARCH` → `GET_RELATED_PHOTOS` → `GET_INFO`). Given a goal, the user simulator draws an acceptable dialog action based on a probability distribution, which is defined with NLU intents (*e.g.*, `REQUEST:GET`, `CONFIRM:SHARE`), slots (*e.g.*, location, time), and memory references. The assistant simulator then takes the output of the user simulator, retrieves the multimodal contexts via the simulation API (*e.g.* obtaining the information of a memory node from the graph, retrieving related memories), and generates natural language generation (NLG) intents, slots and new memory references. The process is repeated until the simulator exhausts every goal in the agenda.

Multimodal Dialog Ontology. Following other task-oriented dialog datasets (Eric et al., 2019; Rastogi et al., 2019; Moon et al., 2020), for COMET we provide the standard dialog annotations such as the intent (NLU & NLG) and slot labels. To accommodate for the complex multimodal nature of the scenarios, we extend the dialog ontology to include memory reference annotations as their corresponding node IDs, which seamlessly annotates both multimodal contexts and language (*e.g.* *'When was our trip to Whistler?'* → `INFORM:GET_INFO.time`, *memories: [8]*). The same notation can be used to refer the memories that are carried over in the dialog context (*e.g.* *'Where did we go after that?'* → `INFORM:GET_RELATED.location`, *memories: [8]*). This proposed fine-grained and unified ontology will allow a systematic approach to study diverse referring expressions in multimodal dialogs.

3.2 Manual Paraphrase

Once the memory graph conditioned dialog flows have been generated, we paraphrase utterances in the dialog flow with the help of human annotators. This allows us to draw utterances from the natural language distribution, thus moving closer to the application. We build an interactive user interface to aid annotators paraphrase utterances from COMET dataset. Specifically, the interface shows the images corresponding to the memories along with the

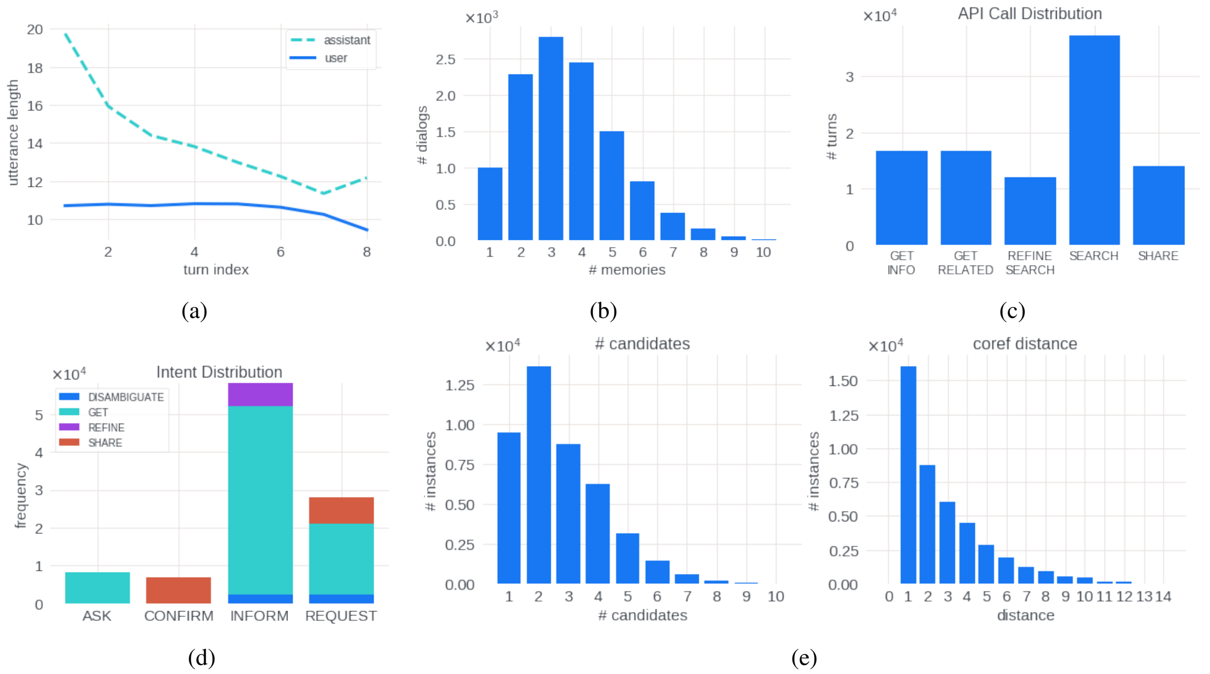


Figure 4: Distribution of (a) utterance lengths with dialog turns, (b) number of memory mentions in each dialog, (c) API calls across the dialogs, (d) dialog acts and activities, and (e) referent candidates (L) and coreference distance (R) between memory mentions.

Total # dialogs	$11.5k$
Total # utterances	$103.4k$
Total # memory graphs	$1.1k$
Avg # words (user turns)	10.7 ± 4.4
Avg # words (assistant turns)	15.4 ± 9.8
Avg # utterances / dialog	8.8
Avg # memories mentioned / dialog	3.5
Avg # memories in graph / dialog	100

Table 1: **COMET Dataset Statistics**

dialog flow and instructs annotators to paraphrase without losing key information such as objects and attributes. See appendix for an example dialog. As paraphrasing utterances is faster, cheaper, and requires little to no domain knowledge on the annotator's part, our two-phase pipeline is much more resource-effective, when compared to collecting multimodal human↔human dialogs and collecting dialog annotations on top (Moon et al., 2020).

3.3 COMET Dataset Analysis

We now analyze the COMET dataset, which contains $11.4k$ dialogs totalling $103.4k$ utterances, grounded in $1.1k$ memory graphs. Tab. 1 presents the overall dataset statistics.

Analyzing Dialogs. Dialogs in COMET use a total of $1.1k$ memory graphs with each containing 100 memories. For every dialog, there are about 3.5 connected memory mentions with the distribution given in Fig. 4b. User and assistant turns average about 10.7 and 15.4 words respectively (distribution in Fig. 4a). It is interesting to note that the assistant responses are significantly longer than the user. As an example, consider the following user utterance *'U: Are there any similar photos from 2020?'* and the corresponding assistant response *'A: Here's one of Laura and Virginia cooking sausages at home, the afternoon of August 26, 2020. It looks like a fun time!'*. This illustrates that the annotators paraphrasing the dialog flows included: (a) details about the retrieved memories to give additional context to the user, thus invoking subsequent connected memory queries (*e.g.*, *'What did we do that evening?'*), (b) chitchat about the memories to make the conversational natural sounding.

Analyzing Dialog Annotations. Our COMET come with annotations at dialog level for dialog state tracking (NLU intents and slots), necessary API calls for assistant, and multimodal coreference resolution. Following Kottur et al. (2021), our intents follow a hierarchy of *dialog acts* (4: `ASK`, `CONFIRM`, `INFORM`, `REQUEST`) and *activities* (4: `DISAMBIGUATE`, `GET`, `REFINE`, `SHARE`). See Fig. 4d for a breakdown distribution over dialog acts and activities. Due to the retrieval nature of our assistant (either memories or associated attributes), a major chunk of the activities are `GET`. Similarly, there are 5 APIs in our dataset (Fig. 4c):

- `SEARCH`: Search using input parameters,

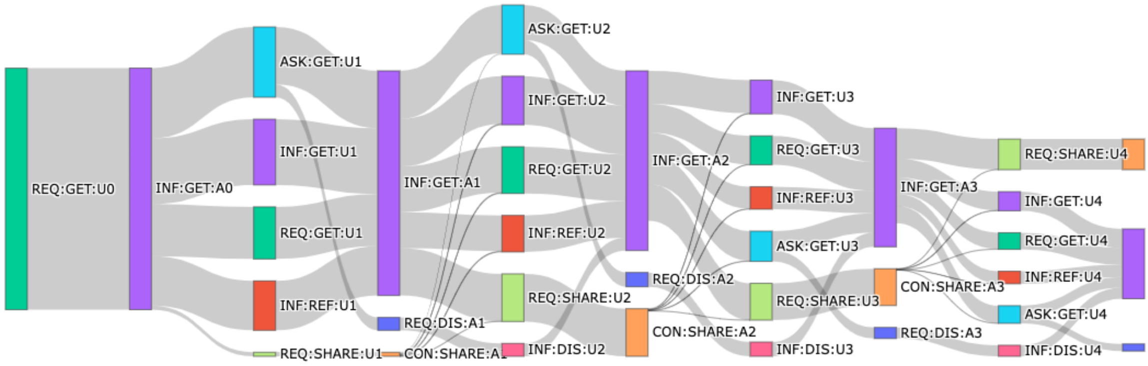


Figure 5: Transition of dialogs acts in COMET for the first 4 turns, for dialog flows generated by our novel multimodal dialog simulator for connected memories. Each block is of the form `ACT:ACTIVITY:[A|U][turn]`, to denote dialog act, activity, user or assistant turn, and turn number, respectively. See text for more details.

- `REFINE_SEARCH`: Build on top of search carrying over existing parameters,
- `GET_INFO`: Seek information about current or previouly viewed memories,
- `GET_RELATED`: Explore other memories similar to the current/prior memories, and,
- `SHARE`: Share it to friends or family,

As expected, `SEARCH` is the most dominant API call in the dataset. Note that the turns with `GET` and `REFINE_SEARCH` API calls elevate the need for conversation in retrieving connected memories, where the user requests for memories similar to the ones already viewed or with additional specifications, respectively. Finally, Fig. 4e visualizes the distribution of number of candidates and utterance difference between the current and the one with referent memory (coreference distance). For turns requiring coreference resolution, the average number of candidates is 2.7 at a distance of 2.9 utterances. Though a majority of referents are naturally 1 utterance away (previous turn), the long tail (even up to 10+ utterances) indicates the presence of challenging multimodal coreferences.

Analyzing Dialog Flows. As mentioned earlier, the multimodal dialog simulator generates the dialog flows during the first phase of our data generation. We visualize these dialogs flows in Fig. 5 for the first four dialog turns, where each block denotes an intent at a particular turn and the grey stripes denote NLU intent transitions in subsequent turns. The width of the stripe is proportional to the frequency of the transition. For brevity, each block is label as `ACT:ACTIVITY:[A|U][turn]`. The high branch-off factors for these intents capture the diversity of the dialogs flows in our dataset, which is desirable in building a robust dialog system.

4 Task Formulation

To benchmark progress of conversational models towards the goal of assisting users in interactively querying connected memories in a meaningful way, we propose four main tasks for COMET. Tab. 2 outlines the task formulations along with the corresponding evaluation metrics.

4.1 Assistant API Call Prediction

The first step in executing any query on connected memories successfully is to understand the user utterance in the context of the dialog history and multimodal information, and predict the right API call. For instance, a query like *'When was the last time I was here?'* should result in a `GET_INFO` API prediction. Note that errors in API call prediction cascade through the model pipeline resulting in an incorrect or unrelated response from the assistant. Thus, this task tests the ability of the conversational agent to predict the right API call. Evaluation is done per each turn through API call accuracy.

4.2 Multimodal Coreference Resolution

Recall that one of our motivations to use conversations for querying connected memories is the ability to support multi-turn queries. In such scenarios, humans often use short-hands or references when the underlying referred entity (referent) can be usually deduced without any ambiguity. As an example, when looking at a particular memory, a follow-up *'When was the last time I was here?'* is intuitive and natural, whereas *'When was the last time I was at Waikiki Beach, Hawaii?'* requires the user to remember the name and use it in the query, making it cumbersome.

Therefore, the model must be able to handle multimodal coreferences in order to field such queries effectively. The input for this task includes the dialog history, multimodal context, and all the memo-

Task Name	Goal	Evaluation
1. Assistant API Call Prediction	Given user utterances, predict the right API call necessary to execute the query.	Classification accuracy
2. Multimodal Coreference Resolution (MM-Coref)	Given user utterances, resolve referent memories to their canonical ID(s) as defined by the memory graph.	Coref Precision / Recall / F1
3. Multimodal Dialog State Tracking (MM-DST)	Given user utterances, track user belief states across multiple turns.	Slot Precision / Recall / F1
4. Assistant Response Generation	Given user utterances, ground-truth APIs and ground-truth object IDs, generate Assistant responses or retrieve from a candidate pool.	Generation: BLEU; Retrieval: Accuracy@k, mean reciprocal rank, mean rank

Table 2: Proposed tasks and descriptions on our COMET dataset. Please see Sec. 4 for more details.

ries mentioned so far (as coreference candidates). The models needs to thus resolve the reference to one or more of the candidates. We use coreference precision, recall, and F1 to measure performance.

4.3 Multimodal Dialog State Tracking

Due to the multimodal nature of COMET, we adopt multimodal dialog state tracking (MM-DST) used in (Kottur et al., 2021) as one of our tasks. To elaborate, slots in our dataset can be grounded in the multimodal context information and requires reasoning through the current or previously viewed memories. For instance, a query like *'Where did we go from here?'* requires the slot value to be the currently viewing memory. This implies that the dialog states can contain non-textual tokens (*e.g.*, memories), thus making it multimodal. In order to measure the performance in this task, we use slot recall, precision, and F1 scores. Note that unlike (Kottur et al., 2021), we drop evaluating for dialog act prediction since `GET` has an overwhelming majority due to the nature of the problem.

4.4 Assistant Response Generation

This task evaluates the ability of the model to either generate a response or retrieve from a pool of candidates, given dialog history, ground-truth APIs & results, belief states, and multimodal contexts. Though the model has access to API results, producing a natural language utterance to describe it within the flow of the dialog is still a difficult task.

We evaluate this task in two different ways: (a) *Generative*, where the model produces the response similar to a conditional language model. We use BLEU-4 (Papineni et al., 2002) to measure performance by comparing the generated response to the ground truth, and (b) *Retrieval*, where the model ranks a list of randomly pooled candidate responses (unique to a turn) along with the ground truth. Retrieval metrics like recall@k ($k = \{1, 5, 10\}$), mean rank, and mean reciprocal rank are used.

Model	1. API Call	2. MM-Coref	3. DST	4. Gen.
	Acc↑	Coref F1↑	Slot F1↑	BLEU↑
GPT2-Text	**87.6**±0.8	72.2±1.5	**89.5**±0.8	0.346±0.007
GPT2-MM	83.3±0.9	**80.3**±1.3	68.4±1.3	**0.397**±0.009

Table 3: Baseline performances for GPT-2 models: text-only (text) and multimodal image features (MM). **(1) API Call Prediction (API Call)**, via classification accuracy, **(2) Multimodal Coreference Resolution (MM-Coref)**, via coref prediction F1, **(3) Dialog State Tracking (DST)**, via slot F1, **(4) Response Generation** via BLEU. ↑: higher is better.

5 Modeling & Empirical Analysis

We now perform preliminary empirical evaluation and analysis for the proposed tasks by training baselines. Detailed modeling work is left as future work.

Dataset Split. The dataset is randomly divided into: train (70%), val (15%), and test (15%). For our experiments, models are trained using train split and performance is reported on test, while val is used to pick the model hyper-parameters.

Notations. We follow the notation established in (Kottur et al., 2021), where each dialog of length N_r rounds is represented as $\mathcal{D} = \{(U_i, A_i, M_i, B_i)\}_{i=1}^{N_r}$ with:

- U_i: User utterance at turn i
- A_i: Assistant utterance at turn i
- M_i: Multimodal context, *i.e.*, memory graph and memories retrieved in the previous turns,
- B_i: Multimodal belief state, a semantic parse of U_i (intent, slot, memory references).

Therefore, given the current user utterance (U_t), dialog history $H_t = (U_i, A_i)_{i=1}^{t-1}$, and the multimodal context (M_t), a COMET agent should predict the user belief state B_t and the natural language response A_t for every dialog turn t.

Baselines. Causal language models pretrained on large datasets have shown a lot of promise in multimodal and text-only task-oriented dialog modeling,

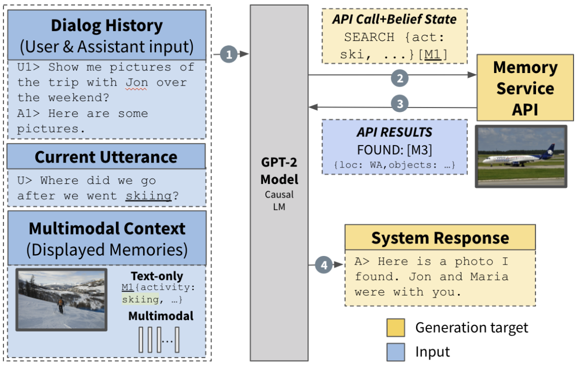


Figure 6: Baseline GPT-2 models for COMET. (1) Given the dialog history, multimodal context, and current user utterance, the model predicts the API call and belief state at the current turn, (2) The API call is executed and (3) the results are fed back into the model, (4) Finally, model produces a natural language response. As shown, GPT2-text uses attribute strings to represent memories, while GPT2-MM use image features.

when finetuned on the downstream task (Hosseini-Asl et al., 2020; Peng et al., 2020; Kottur et al., 2021; Moon et al., 2020). Following this popular approach, we adopt the transformer-based GPT-2 (Radford et al., 2019) model and jointly train it for API prediction, MM-Coref, DST, and response generation tasks, as shown in Fig. 6. In particular, we use the 12-layer GPT-2 ($117M$) model and finetune it on dialogs from COMET dataset, using early stopping based on token perplexity (<3 GPU hrs). We use two approaches to capture M_i:
(a) *text-only* (GPT2-text), where previously viewed memories and their attributes are represented as flattened strings. Note that this baseline uses groundtruth activities from the memory graph.
(b) *multimodal* (GPT2-MM), where bottom-up and top-down (BUTD) (Anderson et al., 2018) image features are extracted for previous viewed memories. In essence, BUTD features are a collection of K vectors each representing a salient objects in the image that have been detecting using a Faster-RCNN backend (Ren et al., 2015). We project these $K = 10$ features and feed them as 'visual tokens' while finetuning the GPT-2 model.

Analysis. Tab. 3 summarizes the performance of our baselines on the four proposed tasks. A key observation is that multimodal model GPT2-MM outperforms its text-only variance in MM-Coref and response generation significantly. This is intuitive as multimodal coreference resolution requires understanding the memories beyond the obvious activity label in order to rightly resolve the reference. Consider the query: *'When was the last time I played with my dog here?'*. To resolve to the right memory, the system needs to understand which memory is about playing with the dog towards which a mere activity label *throwing frisbee* might be insufficient. For a similar reason, additional multimodal features improve response generation, especially to include chit-chat. On the other side, GPT-Text does better on API call prediction and capturing the dialog state suggesting complementary benefits offered by each of these models.

6 Conclusion

We present a novel dataset for the dialogs for connected memories, COMET, with $11.5K$ user↔assistant dialogs ($103K$ utterances) grounded on the memory graphs. We present a novel multimodal dialog simulator, which generates simulated dialogs grounded on diverse memory graphs that are automatically configured. Our empirical analysis demonstrates many new challenges that our COMET dataset brings, highlighting new directions of research in this area.

Limitations. The generalizability of COMET is naturally bounded by the underlying graph simulator, especially around memory attribute labels of place, people, and time. However, we justify this as follows: (a) Recall that the focus of our work is to enable an assistant that can understand and execute user queries about connected memories through an interactive dialog. Even with the simulated dialog flows, COMET captures several interesting challenges related to multimodal dialog, for instance, coreference resolution and dialog state tracking (as seen in Sec. 3.3 and Sec. 5). This opens the door to new research directions in multimodal conversation, especially in the absence of a readily available large-scale personal photo collection dataset (along with attributes and metadata). (b) Due to the two-stage data collection pipeline, COMET is amenable to data augmentation techniques that can increase the robustness of the downstream dialog model. For instance, the dataset can be easily augmented by replacing named entities in the memory graph and utterances, without changing the flow.

Ethical Considerations. All identifiable faces from the COCO images are blurred using a CV algorithm, mitigating privacy risks. Annotators for our task were employed as full-time and contracted via a leading NLP/linguistics annotation platform.

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7 Supplementary Materials

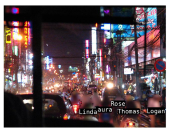
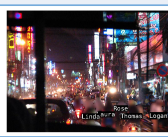
	Utterances	API Annotations / Dialog Acts	Display Images
U	I'm looking for photos from 2020 with my friends.	`SEARCH [time = 2020]`	
A	Here's a photo of your friends snowboarding.	`INFORM:GET <memory: 17>`	
U	Is there a similar photo except with Logan and Linda?	`REFINE_SEARCH [participant = Logan, Linda] <memory: 17>`	
A	Here's a similar memory of your friends at Mount Baldy the afternoon of October 25, 2020, and another of them surfing.	`INFORM:GET <memory: 23, 47>`	 
U	When was that photo?	`GET_INFO (time) <memory: 47>`	
A	Which one are you talking about?	`REQUEST:DISAMBIGUATE`	
U	The second picture you showed me, the one of them surfing.	`INFORM:DISAMBIGUATE <memory: 47>`	
A	This happened at 2:12 PM on October 26, 2020.	`CONFIRM:GET_INFO [time = 10/26/20 2:12PM] <memory: 47>`	
U	Anything with a similar group to this picture except in 2019?	`GET_RELATED [time = 2019] <memory: 47>`	
A	Here is a similar picture of your friends in vehicles. It looks like they are having a great time in both.	`INFORM:GET <memory: 24>`	
U	When and where did this happen?	`GET_INFO (time, location) <memory: 24>`	
A	This occurred at 12:50 PM on December 30, 2019 in Downtown Bay Area, Bay Area, California, USA.	`CONFIRM:GET_INFO [time = 12/30/19 12:50PM] <memory: 24>`	

Figure 7: **Dataset Example**. Dialog labels include intent, slots, and multimodal coreferences.

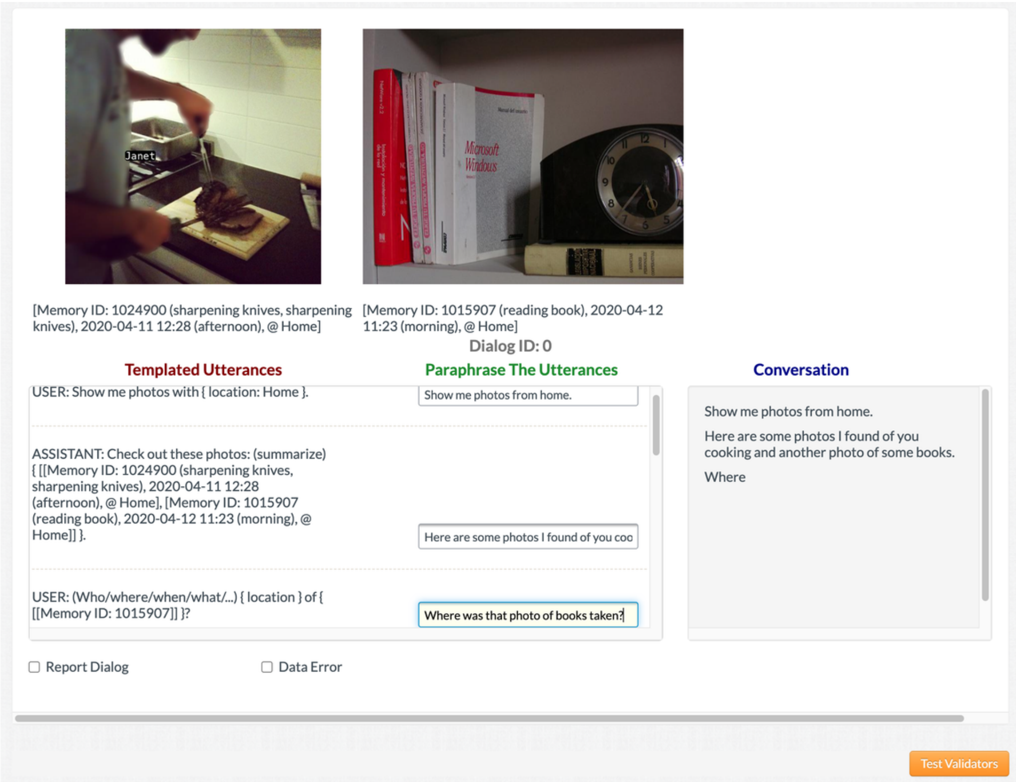


Figure 8: **The annotation tool UI**. Annotators are shown the templated utterances, and a set of photos that dynamically get updated for each turn, based on the pre-generated dialog flows.

Sensitive topics

Any reference to the following topics is inappropriate and should be flagged by checking the “Report Dialog” button:

- PII
  - First Name & Last Name (just one name is not PII)
    - if the first and last name seem to be used in the a slot that would indicate a public figure, such as musical artist, fictional character, or political figure, please **do not mark as containing PII.** If you are unsure check if the name has a wikipedia page. If so, **do not mark as containing PII.**
  - phones numbers, credit card numbers, or social security numbers
  - email
  - Addresses are NOT considered PII unless they are accompanied but another piece of PII (i.e name), in which the combined information would allow you to identify the user.
- Offensive, racist, biased and non-tolerant behavior
  - Profanity, slurs, language that is offensive to any cultural, racial, and religious groups.
  - Bias towards or unequal treatment to any cultural, racial, and religious groups.
  - Anything inconsistent with the values of tolerance and respect for diversity.
- Violence and self-harm
  - Any content which facilitates or encourages violent behavior towards others or any form of self-harm.
  - Descriptions or depictions of violent behavior or self-harm.
  - Any reference to threats or weapons.
  - Any reference to human trafficking, child endangerment or exploitation, or animal abuse.
  - Violent or non-violent crime of any kind
- Sexual or flirtatious behavior
  - Any reference to sexual behavior or materials, legal or illegal.
  - Sexual or flirtatious expressions or innuendo.
  - Explicit or sexual language or physical descriptions.
- Controversial and Polarizing Topics
  - Political opinions or politically charged people or events. General political enquiries are okay, *(e.g. show me political news; Is there any coverage of the election?)*
  - Religion
  - Disputed regions or events
  - Sexuality
  - Cultural practices

Figure 9: Disclaimers shown to the annotators, detailing the escalation path.