1 Introduction

We describe the task of Visual Understanding and Narration, in which a robot (or agent) generates text for the images that it collects when navigating its environment, by answering open-ended questions, such as what happens, or might have happened, here? This task was first explored in Lukin et al. (2018a) where humans wrote narratives answering such questions about images taken by a robot (e.g., Fig. 1) during our human-robot interaction research (Lukin et al., 2018b). The intersection of object identification and text generation has been explored by Das et al. (2017) and Antol et al. (2015), however these works stop short of inferring and narration requirements. Zellers et al. (2018) and Goyal et al. (2017) exploit common sense knowledge of stereotypical, human-centric scenarios in individual images and video clips respectively, yet convey their deductions through multiple choice or slot-filling, rather than generating language or narratives. We briefly survey related current technology and resources, and then sketch our two-pronged approach to bridging the gaps between these fundamental tasks and requirements of the new task.

2 Visual Understanding

Addressing the gap between recognizing particular objects in images and reasoning about why they may be present in a given physical environment requires commonsense knowledge.

2.1 Commonsense Gaps

Commonsense knowledge about objects for computer vision has shown both to improve object and activity recognition and to provide additional information necessary for deeper reasoning (Gupta and Malik, 2015; Yatskar et al., 2016b; Ronchi and Perona, 2015). This type of object knowledge is primarily visual, supporting tasks such as object and activity recognition, as well as transfer learning to visually similar objects and scenes. Such knowledge has included spatial relations (Yatskar et al., 2016a), shape similarity to other objects, and visual attributes such as color (Singh et al., 2018).

However, knowledge humans exploit when analyzing an environment goes beyond visual clues. To interpret Fig. 1 possibly as a kitchen, a system needs not only to recognize the objects, but to know which actions are commonly performed with these objects, and then to infer where such actions may occur. The actions, termed ‘object affordances’ (Gibson, 1979), have been defined in computer vision studies as the combination of: an affordance label, a human pose representation of the action, and a relative position of the object with respect to the human (Grabner et al., 2011; Kjellström et al., 2011; Yao and Huang, 2018; Zhu et al., 2014). Though the latter two can be extracted from visual data, a challenge is how to systematically collect appropriate affordance labels for shared re-use by vision and language researchers, reducing the redundant labor of independent, manual assignments of verbs as labels for small, fixed sets of objects (e.g., sit-on – chair).

2.2 Approach to Bridging Gaps

‘Qualia’ are relations associated with a particular object (Pustejovsky, 1991), including
Agentive (created_by), Telic (functions_as, used_for), Constitutive (part_of, made_of), and Formal (is_a), providing a rich source of commonsense and affordance information, and a framework for disambiguating senses of a word (e.g., book: physical item vs. content). They have been demonstrated as useful knowledge representations for intelligent agents (McDonald et al., 2013; Pustejovsky et al., 2017; Narayana et al., 2018).

A comprehensive set of qualia relations have yet to be defined and organized. We are tackling this challenge and aim to make the qualia usable for visual understanding tasks: qualia have been automatically extracted and evaluated for quality via crowdsourcing (Kazeminejad et al., 2018), then encoded as relations between entities and events in the Rich Event Ontology (REO) (Bonial et al., 2016). Assuming, for example, that the objects in Fig. 1 can be recognized accurately, the resulting list of objects (e.g., pot, cereal) can first be queried for their qualia in REO, to discover: pot is used_for cooking, and cereal functions_as nourishing and is_a prepared_food. These activities with object classes can next be queried for their common locations in REO via their semantic roles, to discover: cooking prepared_food returns kitchen. In this approach, the objects, their affordances, and REO roles, would support the inference that this space functions_as a kitchen.

3 Narrative Building

Once the visual scene is interpreted, we determine what is needed to answer the task question via content selection and narrative generation.

3.1 Generation Gaps

Content selection, or framing, is the relationship between the narrating agent and what they know and choose to talk about (Lönneker, 2005). The choice of appropriate framing device depends on the intended audience of the final narrative. Many recent works in vision treat framing as an observational task, describing the image in a single sentence (Rashtchian et al., 2010; Hodosh et al., 2013; Lin et al., 2014; Chen et al., 2015; Krishna et al., 2016). This limits the scope to the visually observable and restricts what can be learned by extrapolation from the past or to future. With just a handful of open-ended prompts, e.g., what happened, creative scene interpretations can be elicited that go beyond single sentences (Gordon and Roemmele, 2014; Huang et al., 2016; Vaidyanathan et al., 2018).

After assessing what to talk about, the narrating agent must establish how to talk about it. Recent neural vision and text models rely solely on crowd-sourced data for guidance in this phase of narrative crafting (Park and Kim, 2015; Yu et al., 2017; Huang et al., 2016; Fan et al., 2018; Wang et al., 2018). Much can be learned from narratological studies, such as the categorization, combination, and presentation of narrative elements (Labov and Waletzky, 1997; Rahimtoroghli et al., 2013; Niehaus and Young, 2009; Lehner, 1981; Elson, 2012). However, template-based approaches (Montfort, 2007; Callaway and Lester, 2002) and statistical models (Li et al., 2015) that have successfully leveraged these elements for content selection and narrative shaping in text-based story generation, have not yet been applied to visual narration.

3.2 Approach to Bridging Gaps

Lukin et al. (2018a) performed a pilot data collection with framing to elicit a narrative connecting a sequence of images. In our ongoing work, preliminary analysis of human authored narratives about Fig. 1 have found both extrapolation beyond the observable in the image (“[someone intends] to live here at least until they finish the project that they are working on”) and creative causal reasoning for what is not visually depicted in the image (“[someone] is pulling an all-nighter and brought breakfast for the next morning”).

4 Next Steps

The two prongs of our approach provide complementary information for identifying and reasoning about a visual scene, from which succinct and targeted text can be generated in support of human-robot interactions to talk about what happens in the robot’s environment. Qualia encoded in REO provide bottom-up, commonsense knowledge for reasoning, and existing narrative schema can be applied in a top-down manner to formulate narratives, leveraging content from crowd-sourced narrative elements. Our ontology and crowdsourced annotations will be made available to the community, supplementing existing resources.

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1 Ferraro et al. (2015) survey of vision and language resources; framing prompts are similar to those listed here.
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