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Computational Context: Why It's Important, What It Means, and Can It Be Computed?
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Computational Context as Cognitive Priming

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Abstract

Context is the way in which the environment guides how people see, think and act. We argue that context is, in large part, based on cognitive priming, where items or objects that are the focus of attention prime related items in memory. This helps to guide one's thoughts to be relevant to the current situation. Here, we describe our approach to understanding and modeling cognitive context and priming in a computational framework, and discuss how we have leveraged this understanding to improve autonomous systems.

Cognitive priming, also called associative learning, is one of the driving forces behind human cognition. In theories of associative learning, associations tie together related items in memory, allowing items that are currently the focus of attention to *prime* these related items, or make them more available and active in memory. Cognitive priming is traditionally studied for its principal role in memory-based functions such as list learning, memory recall, and classical conditioning (Rescorla and Wagner 1972; Klein, Addis, and Kahana 2005).

In our work, priming is situated in an integrated theory of human cognition that is implemented in a computational framework. The overarching framework models, in part, human working memory, which includes what a person (or a computational model) is thinking of, looking at, or has as their goal at any give time (Trafton et al. 2013). As part of our theory on priming, associations are formed between items that are in working memory at the same time (Thomson et al. 2017); then, the more often items are thought about together, the stronger their associations become. The contents of working memory also serve as the source of cognitive priming: at any given time, items in memory are primed according to the strength of their associations with the current contents of working memory. Importantly, using working memory as the basis for creating and strengthening associations, as well as for spreading priming, creates an integrated view of priming that is based on the model's entire state and all of its modalities (vision, aural, its goals and reasoning, etc.), and can incorporate both semantic and statistical correlation information.

Recently, we have also shown cognitive priming to be a fundamental component in higher-level cognitive processes. Similarity, for example, is a complex mental construct that is critical to tasks such as object categorization (Nosofsky 1992), problem solving (Novick 1990) and decision-making (Medin, Goldstone, and Markman 1995). We have shown that similarity has strong roots in priming; items which more strongly prime one another are typically considered more similar (Hiatt and Trafton 2016), such as items that share semantic features, or are commonly seen together.

Here, we also argue that priming is a critical component of context, where we consider context to be the way in which the environment guides how one sees, thinks and acts. In the past, computational context has taken many forms, many of which involve explicit learning and statistic reasoning (Oliva and Torralba 2007). Here, we propose a complementary form of context based on our computational implementation of cognitive priming. Using this form of context, working memory serves as the source of context; then, highly-primed items are considered to be very strongly relevant to the current context, and slightly-primed items are considered to be only weakly relevant to the current context.

This contextual information can then be leveraged for autonomous systems where context has the potential to help performance. Primarily, we have shown the benefit of this context on object recognition, significantly improving the precision of difficult recognition problems (Lawson, Hiatt, and Trafton 2014). We have also shown that it can effectively identify out-of-context objects, robustly identifying anomalous features in an automated surveillance task (Lawson et al. 2016). In these works, contextual information was a blend of categorization information (objects are primed by the rooms or areas in which they appear, since they appear in working memory at the same time), as well as implicit spatial/co-occurrence information (objects are often primed by other nearby objects, since they are in working memory at roughly the same time). These sources of information are automatically blended and combined by the associative learning mechanisms inherent in our theory.

As robots become more complex, and separate components of robots become more integrated (such a vision vs. task planning), we believe that this cohesive view of priming will continue to be an important source of reasoning about context. It effortlessly explains, for example, why a person (or a robot) is predisposed to see a hammer when looking for one – because hammer is primed by the current goal, and so biases the person or model towards that object. Using these learning mechanisms also results in easy, natural training of context since the model, like people, is designed to learn online as it goes about in the world, and does not require extensive a priori training (Hiatt et al. 2016). Finally, the above approach also connects context with work on how priming affects how people perceive and act in the world in other ways, such as explaining errors that people make on routine procedural tasks (Hiatt and Trafton 2015a), and explaining induced cases of mind wandering (Hiatt and Trafton 2015b). This can potentially increase the effectiveness of contextual models at not only understanding the world around them, but also relating that understanding to the behavior of human partners.

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