Learning from Observation (LfO) is a machine learning paradigm that mimics how people learn in daily life: learning how to do something simply by watching someone else do it. LfO has been used in various applications, from video game agent creation to driving a car, but it has always been limited by the inability of an observer to know what a performing entity chooses to remember as they act in an environment. Various methods have either ignored the effects of memory or otherwise made simplistic assumptions about its structure. In this dissertation, we propose a new method, Memory Composition Learning, that captures the influence of a performer’s memory in an observed behavior through the creation of an auxiliary memory feature set that explicitly models the aspects of the environment with significance for future decisions, and which can be used with a machine learning technique to provide salient information from memory. It advances the state of the art by automatically learning the internal structure of memory instead of ignoring or predefining it. This research is difficult in that memory modeling is an unsupervised learning problem that we elect to solve solely from unobtrusive observation. This research is significant for LfO in that it will allow learning techniques that otherwise could not use information from memory to use a tailored set of learned memory features that capture salient influences from memory and enable decision-making based on these influences for more effective learning performance. To validate our hypothesis, we implemented a prototype for modeling observed memory influences with our approach and applied it to simulated vacuum cleaner and lawn mower domains. Our investigation revealed that MCL was able to automatically learn memory features that describe the influences on an observed actor’s internal state, and which improved learning performance of observed behaviors.