

To The Knowledge Frontier and Beyond:
A Hybrid System for Incremental Contextual-
Learning and Prudence Analysis

by

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Declaration

This thesis contains no material, which has been accepted for the award of any other degree or diploma in any tertiary institution, and that, to my knowledge and belief, this thesis contains no material previously published or written by another person except where due reference is made in the text of the thesis

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Abstract

Increasingly, researchers and developers of knowledge based systems (KBS) have been attempting to incorporate the notion of context. For instance, Repertory Grids, Formal Concept Analysis (FCA) and Ripple-Down Rules (RDR) all integrate either implicit or explicit contextual information. However, these methodologies treat context as a static entity, neglecting many connectionists' work in learning *hidden and dynamic contexts*. This thesis argues that the omission of these higher forms of context, which allow connectionist systems to generalise effectively, is one of the fundamental problems in the application and interpretation of symbolic knowledge.

This thesis tackles the problems of KBSs by addressing these contextual inadequacies over a three stage approach: *philosophically, methodologically* and through the application of *prudence analysis*. Firstly, it challenges existing notions of knowledge by introducing a new philosophical view referred to as *Intermediate Situation Cognition*. This new position builds on the existing SC premise, that knowledge and memory is re-constructed at the moment required, by allowing for the inclusion of hidden and dynamic contexts in symbolic reasoning.

This philosophical position has been incorporated into the development of a hybridised methodology, combining Multiple Classification Ripple-Down Rules (MCRDR) with a function-fitting technique. This approach, referred to as Rated MCRDR (RM), retains a symbolic core acting as a contextually static memory, while using a connection based approach to learn a deeper understanding of the knowledge captured. This analysis of the knowledge map is performed dynamically, providing constant online information. Results indicate that the method developed can learn the information that experts have difficulty providing. This supplies the information required to allow for generalisation of the knowledge captured.

In order to show that hidden and dynamic contextual information can improve the robustness of a KBS, RM must reduce brittleness. Brittleness, which is widely recognised as the primary impediment in KBS performance, is caused by a system's inability to realise when its knowledge base is inadequate for a particular situation. RM partly addresses this through providing better generalisation; however, brittleness can be more directly addressed by detecting when such inadequacies occur. This process is commonly referred to as *prudence analysis*. The final part of this thesis proves the methods philosophical and methodological approach by illustrating how RM's use of hidden and dynamic contextual information, allows the system to perform this analysis. Results show how experts can confidently leave the verification of cases when not warned, reducing brittleness and the knowledge acquisition effort.

This thesis shows that the idea of incorporating higher forms of context in symbolic reasoning domains is both possible and highly effective, vastly improving the robustness of the KBS approach. Not only does this facilitate improved classification through better generalisation, but also reduces the KA effort required by experts. Additionally, the methodology developed has further potential for many possible applications across numerous domains, such as Information Filtering, Data Mining, incremental induction and even reinforcement learning.

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