A Multi-Agent architecture for collaborative reasoning in workflows

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Abstract. This paper presents an approach towards a multi-agent architecture utilising agents that operate on different problem angles and individually constitute a reasoning mechanism towards a global optimal solution. A multi-agent framework is proposed based on the Blackboard architecture coordinating the process and orchestrating intelligent agents towards the identification and construction of a suitable solution. This framework could be applied in a similar context towards remedial actions in the context of business workflows. For this experiment a simple evaluation is presented using the IRIS dataset utilising case-based reasoning and artificial neural network intelligent agents, coordinated by the proposed framework. Finally, the future steps are presented towards large scale agent reasoning and optimization.

Keywords: Case-based Reasoning, Intelligent Agents, Business Workflows, Blackboard architecture, Artificial Neural Networks.

1   Introduction

Business process workflows constitute a large part of corporate operations, working as models for service systems, coordinating actions and different roles in complex, dynamically changing environments. Business processes can define hierarchies, relationships among stakeholders and codify in detail what is expected among internal / external organisational layers [15].

Business processes are being used increasingly to manage and automate processes since they offer the necessary standardisation to fulfil organisational needs. Standards like the OASIS Business Process Execution Language (BPEL), short for Web Services BPEL (WS-BPEL) [16] and the Workflow Management Coalition (WfMC) backed XML Process Definition Language (XPDL) have contributed extensively to the standardisation and interchange of Business Process definitions for different organisational workflow products and systems [17].

The existing standards for business processes offer the ability to define the process. However, its following execution is of great importance to any involved stakeholders (mainly managers) since by following the executed traces (workflows) can argue whether a process fulfils its purpose, the presence of systems failures, and/ or the

compliance of user behaviour to the standards of the business process. The executed workflows can indicate a variety of signs for existing or future process malfunctions, therefore it is important to be able to capture them and apply appropriate action. Work on the intelligent monitoring of business workflows [2, 18, 19] has shown that case-based reasoning could be used effectively to monitor them and trigger appropriate actions on demand. This could be expanded further with the application of multiple intelligent techniques to complementary reason and attempt to assist in the articulation of a complete solution for an experienced problem.

Intelligent agents seem a solution for managing, sharing and utilising knowledge as extracted from their operational environment. Agents can learn from their environment and improve their reasoning mechanisms while contributing / improving the knowledge perception standards of their utilised (control) mechanism. This leads to autonomous systems with elements of self-adaptation and self-management. Work in the area shows examples from the work of Franklin, etal. [20, 21] that was conducted for the U.S. navy, the work of Franklin & Graesser [22], towards autonomous knowledge elicitation, environment learning [23] and others.

This work proposes an intelligent multi-agent framework that could utilise the aggregated knowledge of its variants (agents) towards the formulation of a better global solution compared to what each single agent could suggest. The structure of this work is as follows: Section 2 presents the relevant work in terms of intelligent agents and application framework, Section 3 describes the research methodology behind the work, Section 4 shows the conducted experiments and finally Section 5 presents the conclusions and the future work.

2 Relevant Research work

Multi-agent frameworks have been used widely in different contexts, in order to deploy distributed multi-agent systems both for traditional and AI applications. Examples can be seen in areas like process control [1], business workflows [2], robotics [3, 4] and intelligent system control [5, 6]. Many of these frameworks have been designed and used in general-purpose context, however there also examples of more domain specific with most popular amongst them the DMASON, JADE, JACAMO and DARBS [6].

Substantial part of the current work relies mainly on the blackboard architecture due to its architectural design properties e.g. JACAMO [7] and DARBS [8]. Heterogeneous Knowledge Sources (KSs), modularity, flexibility, extensibility, efficiency and quality, opportunistic cooperation, software reuse and separate coordination controller are a few of the characteristics [9] that make blackboard architecture popular among other software engineering infrastructures. Examples of the latter include ARCHON, OSACA and DIDE, ADEPT [10] etc., that may have limited applicability due to domain specific characteristics. Blackboard architecture due to its native characteristics seems more appropriate to build massive and de-centralised multi-agent implementation systems that are able to control the process of the problem decomposition and give fast and more accurate partial solutions [11].

Agents work on either an individual or collaborative basis, collecting knowledge from their environment, becoming experts over a period of time on a problem related to their knowledge area. In a multi-agent environment different agents could provide different solutions to a problem or part of it based on their expertise. However, this may not be the best compared to the global knowledge that the overall multi-agent system could had. As a result the notion of trust and confidence at agent level emerges in an attempt to address whether the produced solution for a specific problem is the most complete. Trust has been conceptualized in an individual-level and system-level in regards to an agent's aims and objectives, interactions, service efficiency and quality of knowledge [12, 13].

Quantification of trust according to the quality of knowledge provided by an agent has been already proposed for multiple and heterogeneous case-based reasoning systems [14]. However, such approach deals only with multiple CBR sources, that provide the knowledge, hence the experience needed to calculate trust towards an agent. In this paper we will present an approach that attempts to measure the trust of the system and confidence towards different AI agents with variant perspectives, specialisation and different approach while dealing with their investigated case.

3   Research Methodology

This work investigates whether there can be multi-agent multi-reasoning collaboration while developing a semi-autonomous artificial intelligence (AI) approach. This section presents an approach towards developing the suggested system.

Section 2 has shown how blackboard architecture has been used as a backbone infrastructural framework for different representational, reasoning and multi-purpose applications e.g. HERSAY- II, HERSAY III [15] and BIICS [5]. Blackboard seems a plausible choice for the development of componentised systems since it offers substantial differentiation to the key structure components of knowledge sources. Accordingly this architecture allows the modification of core components on demand, giving the ability to develop large multi-agent systems for analysis and reasoning of business workflows [2].

Our approach towards an architectural structure for intelligent multi-agent reasoning comprises four main elements. This structure comprises four components (as seen in Figure 1): a blackboard backbone component (job controller), an agent coordinator, a trust component and a confidence evaluator one. The aim of the architecture is to achieve an accurate classification of each agent (expert in a certain domain area) that ideally contributes to a close to complete solution for an investigated problem. The evaluation of the system trust to any existing agents may be regarded as foundation for achieving such. A challenge for the proposed architecture is that it should accommodate multiple reasoning agents upon whom it does not have information regarding their experience of an investigated domain.

The process followed when a problem investigation is carried out is the following: a new case is presented to the controller; the controller as its first action it attempts to identify which expert is more qualified to contribute to the solution of the problem.

The trust for each agent (expert) is being calculated and the controller assesses agents based on their trust priority. Following this stage a priority schedule takes place in terms of which agent and at which percentage will contribute to the provided solution. Figure 1 present visually the system workflow.
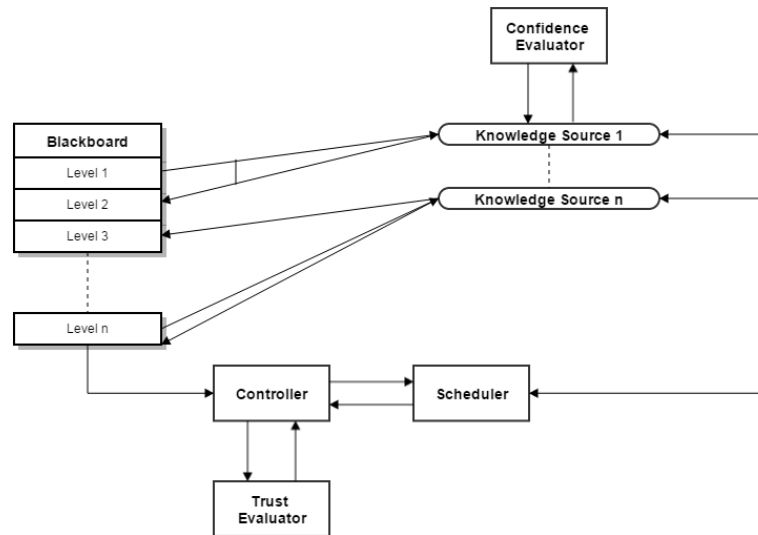

Fig. 1. De-componentisation of the architecture for multi-agent intelligent reasoning

Trust calculation is a process that the controller undertakes before finalising the selection of relevant solution-wise agents. Before each execution the controller enquires the confidence levels of each agent regarding a required solution. Following this stage when an agent declares that is confident enough to contribute to the specific problem, the controller reschedules the agent priorities and the execution begins. After each execution cycle the agent's trust is being updated at controller level in order to refine the selection criteria for any future iteration.

In order to evaluate the suitability of the architecture approach proposed in this paper, a number of experiments were conducted with the Iris Flower dataset, from the UCI machine learning repository. Intelligent agents were included to our framework as single entities, had received complete training cycles and became expert in regards to their trained system. Each train cycle consisted of three classes from the iris flower dataset. At the end, the agents were challenged with different flower attributes through requests on the blackboard in order to check whether the system was able to classify the species of the flowers efficiently.

As a second stage, an integration of two heterogeneous agents should be questioned, having each one trained individually. Training cycles included different flower classes, in order to distinguish them as a distinct expert entity inside the framework. To be more specific, one agent received the first class as a training case base and the

second the rest of the dataset. The agents were challenged with different flower species attributes through a blackboard request to challenge whether the multi-agent system was able to classify the species efficiently.

4 Results and Trust Evaluation

In order to evaluate the proposed approach experiments were conducted in two stages: The first stage included experiments with singe agents in order to investigate their individual reasoning capability within a multi-agent system, whereas at a second stage a hybrid version of the system allowed each agent to become an expert in different domains of the problem.

For this study, two different families of artificial intelligent agents were used: based on Cased-based Reasoning and Pattern Recognition Neural Networks. Both of the agent families were trained using the Iris Flower dataset. The blackboard multi-agent framework has used JColibri [24] framework for the CBR components and the ANN algorithm provided by Matlab.

The dataset used includes 150 samples divided into three flower classes where the first class is linearly separated from each other and the rest of the classes are not. A modification that was necessary to be made is that an Id attribute needed in order for the cases to be more flexible while being processed by the AI agents.

4.1 Single agent experiment

The dataset consisted of a set of 150 cases, divided into three flower classes. Figure 2 presents through scatter plot the dispersion of the attributes. A set of cases where extracted from the original dataset in order to evaluate the efficacy of our agents-experts. 30 out 150 samples where used to serve as case studies, without any case being modified from the original structure.
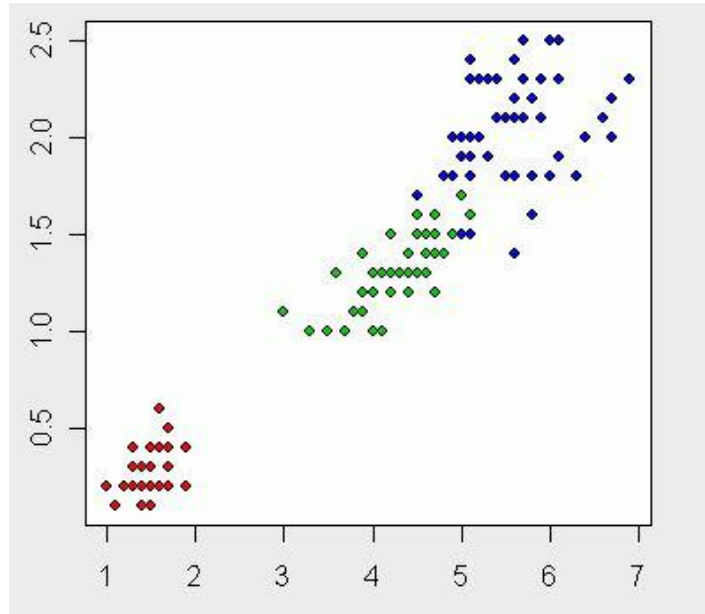
Fig. 2. Iris Flower Dispersion

CBR agent was a Single-Shot system that made suggestions based on the query of the top five matches and allowed decision making among the most similar for revise and retain based on the similarity percentage of each retrieved case [Figures 3, 4]. The first cycle of training included the 80% of the flower species and 20% of each class used as a test set. The second training cycle included a set of 33,3 % of the dataset samples and another 66,7 % (last two flower classes) were used as a test set.
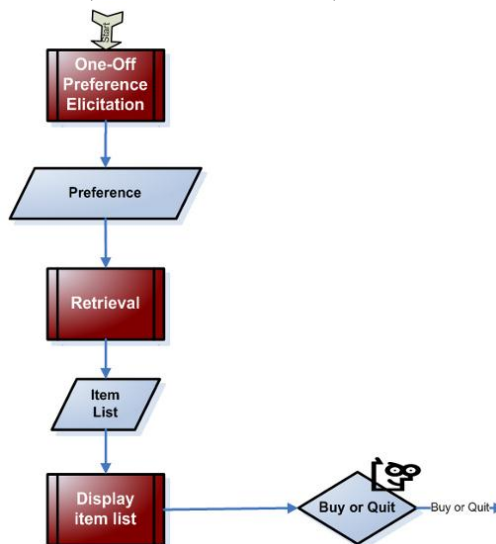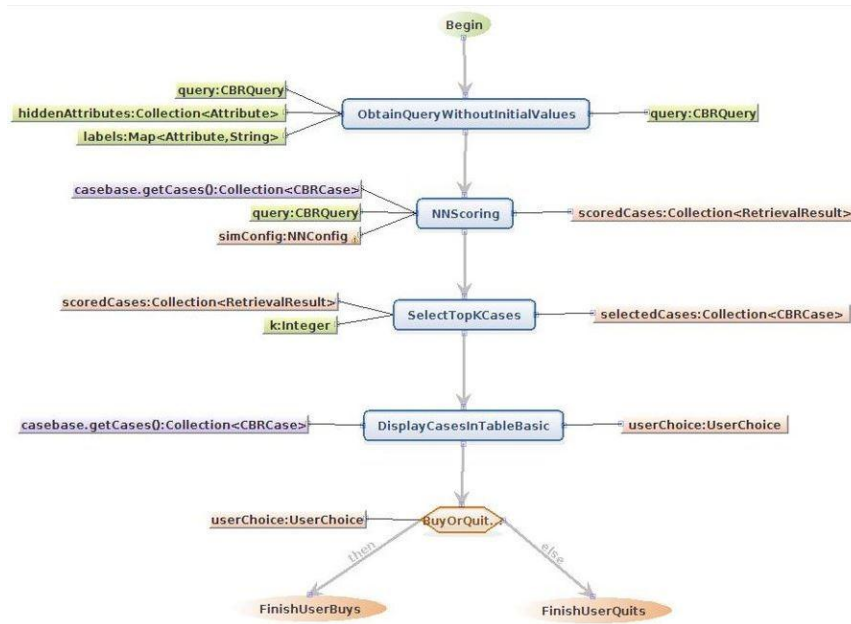
Fig. 3. jColibri's single shot approach

Fig. 4. Single shot's CBR cycle

For the ANN a similar training was followed, using different class of the dataset samples for training and testing. Matlab framework was used for the generation and training of a pattern recognition and classification ANN algorithm.

The used algorithm had the same characteristics both for the complete flower and the single class flower-set training, with that being 10 hidden neurons and the same network topology [Figure 5]. For the first training cycle 75 % of the dataset was used for training, 15 % used for the validation and another 10 % used for testing. The same percentages apply for the flower class one training.
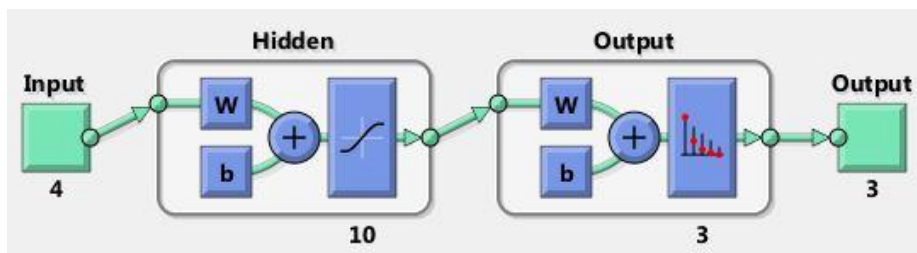

Fig. 5. Neural Network Topology for the ANN agent

For the first cycle of the experiment the CBR agent mechanism was able to classify 9 out of 10 examined cases for the 1st and 2nd class, while 3rd class had significant decrease in accuracy. The reason was the lack of linear separation among classes two and three. As a result CBR agent had several false positives [Table 1] [Figure 6].

	Cases correctly classified (70%≤ sim (C$_n$) ≤86%)	%	Cases Uncertainty (sim (C$_n$) ≤ 50%)	%
1st Class	9/10	90%	1/10	10%
2nd Class	9/10	90%	1/10	10%
3rd Class	5/10	50%	5/10	50%

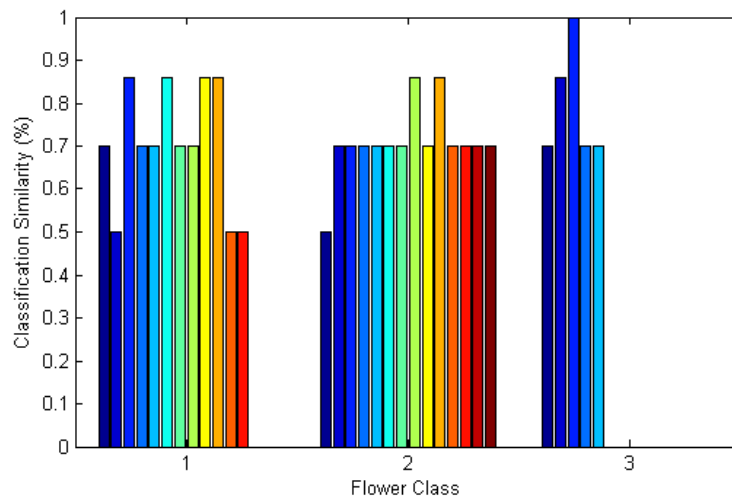**Table 1.** CBR single agent classification

Fig. 6. CBR classification for the IRIS dataset.

On the contrary, the ANN agent was able to classify successfully all the examined cases across the three classes [Table 2], [Figure 7]

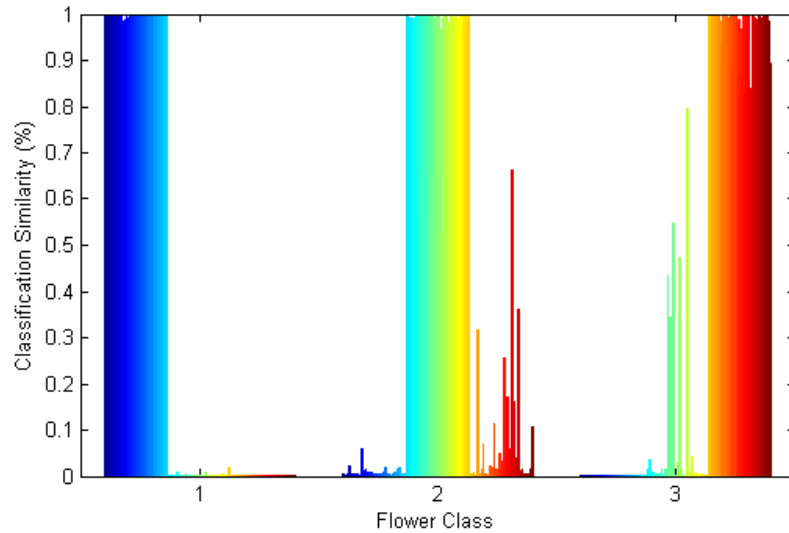|	Cases correctly classified (Average %)
1st Class	0,998398232
2nd Class	0,991072521
3rd Class	0,969773506

Table 2. ANN classification

Fig. 7. ANN Class Flower Classification

4.2 Multi agent experiment

For the second stage of the experiments both agents were challenged to work collaboratively towards in order to determine whether their combined classification was producing more accurate results. The agents were challenged with different flower species attribute through blackboard requests and as a result the issue of the "best decision" was raised.

The issue raised had to do with the competence of the agents, in terms of whether or not an agent's choice was in favour to the other leading to a final decision of the most suitable for a required task. Empirically, we were able to figure out that the non-linearity separation was the reason for the false results of the CBR. So, as a result the ANN agent was chosen to address the classification challenge and resolve any issues.

5 Conclusions

This paper has shown an initial approach to multi agent reasoning using a number of intelligent techniques over the IRIS sample. Experiments with single and multi-agent reasoning have been shown successful and the system has shown ability to develop trust over time. Trust has been measured in terms of successful classification of the case's genre over a time.

This work can be considered as a promising step towards hybrid reasoning using intelligent solutions. Future steps will focus on expanding hybrid reasoning to more

complex systems and workflows as well as investigate further the opportunity for effective training, communication and collaboration of the involved agents, as well as investigate more carefully the concepts of trust, confidence measurement and overall evaluation. Additionally future work aims to benefit from the experience that agents build over time by operating in specific fields, harnessing experience and (re)using it when called to classify an investigated case.

6   References

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