

Bridging the Lesson Distribution Gap

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Abstract

Many organizations employ *lessons learned* (LL) processes to collect, analyze, store, and distribute, validated experiential knowledge (*lessons*) of their members that, when reused, can substantially improve some evaluation measures of targeted organizational decision processes. Unfortunately, deployed LL systems do not facilitate lesson reuse, and thus fail to bridge the *lesson distribution gap* between the lesson repository and targeted decision processes (i.e., they fail to bring lessons to the attention of users when and where they are needed and applicable). Our approach for solving this problem, named *monitored distribution*, tightly integrates lesson distribution with these decision processes. We describe a case-based implementation of monitored distribution (ALDS) in a plan authoring tool suite (HICAP) and evaluate its utility in a simulated military planning domain. Our results show that monitored distribution can significantly improve plan evaluation measures for this domain.

1 Introduction

Identified lessons encode verified knowledge gained from experience that teach improvements for a work practice [Fisher *et al.*, 1998]. Many organizations develop *lessons learned* (LL) systems to assist with collecting, analyzing, storing, distributing, and reusing lessons. A frequent motivation for these efforts includes saving lives by preventing recorded catastrophes from recurring [DOE, 1999]. Lessons are usually in unstructured text format, and distribution is commonly supported using standalone full-text/keyword retrieval tools that require users to “pull” lessons from a repository. Unfortunately, problems with text representations and with this approach to distribution negatively impact lesson reuse, causing these systems to suffer widespread underutilization [Weber *et al.*, 2001]. In particular, they are responsible for what we term the *lesson distribution gap*, which exists when, because an organization fails to properly promote lesson reuse, available lessons are not deployed when and where they are needed by members of that organization.

At least three approaches exist to eliminate this gap. First, identified lessons can, under some conditions, be incorporated

directly into *doctrine*, which defines the processes to be employed by an organization’s members. This causes doctrine to be updated, corresponding to the knowledge contained in the lesson. For example, the Army’s CALL Center [CALL, 2001] deploys teams that consist of both lesson analysts and doctrine experts, which facilitates incorporating lessons into doctrine. However, not all lessons can be incorporated into rule-like doctrine (e.g., because they may be true exceptions), and not all organizations have close working relations between doctrine and lessons learned personnel.

A second way to bridge this gap involves manually “pushing” lessons to potential users, such as via list servers (e.g., SELLS, 2000). Pushing lessons can be automated, at least in part, by intelligent spiders. Some spiders can even build and refine user models to tailor their search for information relevant to a user’s interests. Two of the Department of Energy’s sites already employ portals that provide spiders [SELLS, 2000], and this idea should quickly become popular at lessons learned centers.

Although useful, spiders are not integrated with the decision support processes that stored lessons are intended to support. That is, after retrieving lessons with a spider, users must characterize the situations for which they are useful, recall them when they encounter an applicable decision support context, and interpret them correctly so that their suggestion/recommendation is properly applied. These are challenging tasks, requiring a high level of expertise and time that most users do not have.

We investigate a third approach to bridging the lesson distribution gap that involves tightly integrating the lesson repository with a decision support tool. Our approach, detailed in Section 2, requires inserting a monitor into the decision support process so that it can determine when a lesson’s conditions are well matched by a decision context. In Section 3, we describe a case-based implementation of this *monitored distribution* approach in ALDS (Active Lesson Delivery System), a module of the HICAP plan authoring tool suite [Muñoz-Avila *et al.*, 1999]. We describe ALDS’s evaluation in Section 4, where we provide evidence that it can significantly improve performance measures for HICAP-generated plans for a simulated military (i.e., noncombatant evacuation operations (NEOs)) planning domain.

Based on a recent survey [Weber *et al.*, 2001] and analysis of the first workshop on Intelligent Lessons Learned Systems [Aha and Weber, 2000], we believe that monitored distribution is

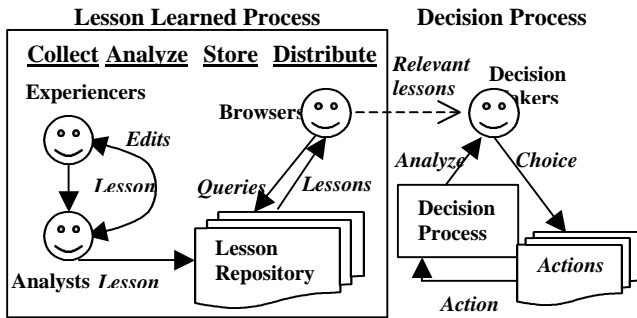


Fig. 1. Most lessons learned processes are separated from the decision processes they support.

novel with respect to deployed LL systems, and has great potential for deployment. We discuss the implications of our findings and future research issues in Section 5.

2 Monitored Lessons Learned Processes

A **lessons learned process** (LLP) is a type of knowledge management process that [Davenport and Prusak, 1998] implements a strategy for collecting, analyzing, storing, distributing, and reusing lessons to continually support an organization's goals. A **lesson** is a knowledge artifact that represents a validated (i.e., factually and technically correct) distillation of a person's experience, either positive or negative, that, if reused by others in their organization, could significantly improve a process in that organization. In particular, it identifies a specific design, process, or decision that reduces or eliminates the potential for failures and mishaps, or reinforces a positive result [Secchi *et al.*, 1999]. A lesson is often confused with a **lessons learned**, which refer to the beneficial reuse of a recorded lesson rather than the lesson itself.

Many large government and private organizations have dedicated lessons learned groups that implement a LLP, including several dozen groups in the DOD, DOE, and NASA alone [Weber *et al.*, 2001]. A primary motivation for recording lessons is to capture *tacit* experiential knowledge from an organization's employees whose knowledge might be lost when they leave the company, shift projects, retire, or otherwise become unavailable. LLPs typically target decision-making or execution processes for various types of user groups (i.e., managerial, technical) and organizations (e.g., commercial, military). In this paper, we focus on managing lessons to support *planning* processes.

Flowcharts describing LLPs abound; organizations produce them to communicate how lessons are to be collected, analyzed, and distributed [SELLS, 2000; Fisher *et al.*, 1998; Secchi, 1999]. Figure 1 displays a typical LLP, composed of the five sub-processes mentioned above, where reuse does not take place in the same environment as the other sub-processes.

Existing, deployed *LL systems* do not support all processes in a LLP. In particular, organizations typically do not develop software to support verification or reuse. Instead, they use electronic submission forms to facilitate lesson collection, and use a standalone retrieval tool for lesson distribution [Weber *et al.*, 2001]. Users interacting with this standalone tool are expected to browse the stored lessons, studying some that can assist them with their decision-making process(es). However, based on our interviews and discussions with members of several LL organizations (e.g., in the Navy, Joint Warfighting

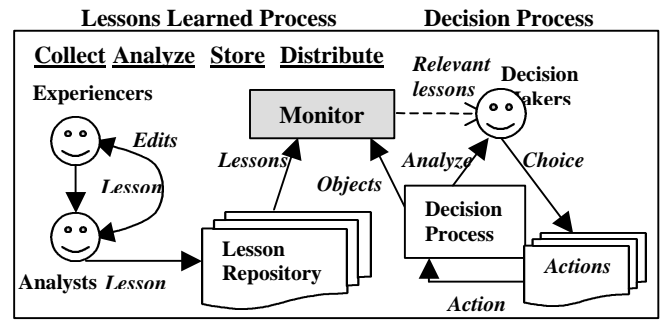


Fig. 2. Monitored lesson distribution integrates the lessons learned process with lesson-targeted decision processes.

Center, Department of Energy, and NASA), and many intended users, we found that they do not use available standalone LL systems, which are usually ineffective because they force users to master a *separate* process from the one they are addressing, and impose the following unrealistic assumptions:

- Users are convinced that using LL systems is beneficial, and can find them.
- Users have the time and skills to successfully retrieve relevant lessons.
- Users can correctly interpret retrieved lessons and apply them successfully.
- Users are reminded of the potential utility of lessons when needed.

We believe that lessons should be shared when and where they are applicable, thus promoting their reuse. This motivated us to develop an architecture for proactive, integrated lesson distribution (Figure 2). In this *monitored distribution* approach, reuse occurs in the same environment as other sub-processes; the decision process and LLP are in the same context. This embedded architecture has the following characteristics/implications:

- The LLP interacts directly with the targeted decision-making processes, and users do not need to know that the LL module exists nor learn how to use it.
- Users perform or plan their decision-making process using a software tool.
- Lessons are brought to the user's attention by an embedded LL module in the decision-making environment of the user's decision support tool.
- A lesson is suggested to the user only if it is applicable to the user's current decision-making task and if its conditions are similar to the current conditions.
- The lesson may be applied automatically to the targeted process.

This process shifts the burden of lesson distribution from a user to the software, but requires an intelligent "monitoring" module to determine whether/when a lesson should be brought to a decision maker's attention.

3 Implementation

We implemented the monitored distribution process in ALDS, a module of HICAP [Muñoz-Avila *et al.*, 1999]. This section details HICAP and then ALDS.

3.1 Plan authoring using HICAP

HICAP (Hierarchical Interactive Case-based Architecture for Planning) is a multi-modal reasoning system that helps users to refine a planning hierarchy. A hierarchy is represented as a triple $H = \{T, \pi, \cdot\}$, where each task $t \in T$ is defined by its name t_n , π defines a (partial) ordering relation on tasks, and $t_1:t_2$ means that t_1 is a parent of t_2 in T . Task hierarchies are created in the context of a state $S = \{\langle q, a \rangle^+\}$, represented as a set of question/answer pairs.

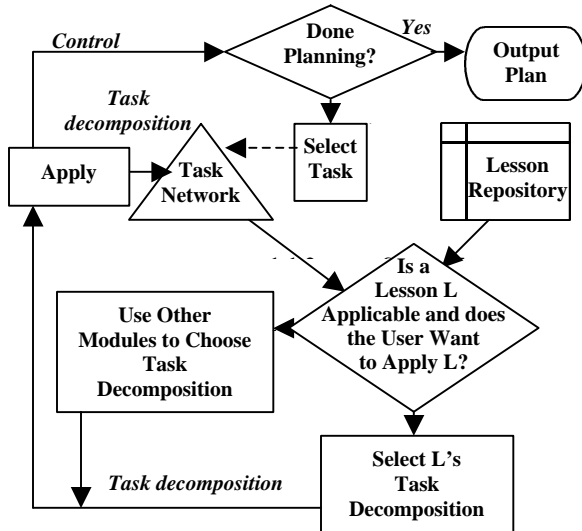


Fig. 3. HICAP's lessons distribution sub-process, implemented in ALDS, during plan elaboration.

Although HICAP manipulates several objects (e.g., resources) and decisions (e.g., how to resolve a resource conflict), we limited ALDS to only perform task substitution, where substituted tasks can then be decomposed using HICAP. HICAP provides three ways to decompose tasks into subtasks. First, it supports manual task decomposition. Second, users can select a task t to decompose and use HICAP's conversational case retriever (NaCoDAE/HTN) to *interactively* select a stored task decomposition for t , assuming that specific cases exist for decomposing t . This involves a conversational interface, where the user views displays of top-ranking solutions and unanswered questions, and can iteratively answer any of the displayed questions (which adds a $\langle q, a \rangle$ pair to S and updates the two displays), and can end the conversation by selecting a displayed solution (i.e., a task decomposition). Third, users can select a generative planner (SHOP) to *automatically* decompose t , assuming methods or operators exist for decomposing t .

3.2 Monitored lesson distribution using ALDS

Planning tasks (e.g., for military operations) involve several decisions whose affect on plan performance variables (e.g., execution time) depends on a variety of state variables (e.g., available friendly forces). Without a complete domain theory, HICAP cannot be guaranteed to produce a correct plan for all possible states. But obtaining a complete domain theory is often difficult, if not impossible. In addition to representing typical experiential knowledge, lessons can help fill gaps in a domain theory so that, when reused appropriately during planning, they can improve plan performance. This is the motivation for applying lessons while using HICAP.

Figure 3 summarizes the behavior of ALDS (Active Lesson Distribution System), the monitored distribution module. ALDS monitors task selections, decompositions, and state conditions to assess similarities between them and the stored lessons. When a stored lesson's applicable decision matches the current decision and its conditions are a good match with the current state, then the lesson is brought to the user's attention to influence decision making. When a user implements a prompted lesson's task decomposition (i.e., reusing the lesson), the current task hierarchy is modified appropriately.

Instead of representing lessons using all six of the characteristics of an idealized lesson representation [Weber *et al.*, 2001], we instead represented lessons using NaCoDAE/HTN's representation for task decomposition cases. That is, a lesson is indexed by the *task* that it can decompose and a set of $\langle \text{question}, \text{answer} \rangle$ pairs defining its *conditions*, and contains a *suggestion* (e.g., a task substitution). Thus, if the conditions are a "good" match to the current planning state, then the user should consider decomposing the current task into the lesson's suggested subtasks. We borrowed NaCoDAE/HTN's similarity function for cases, and used a thresholded version to define "good" (i.e., determine when a lesson should be prompted to a user). In future implementations, lessons will be able to represent suggestions that, when applied, will not be limited to task substitution. For example, a lesson might suggest a task decomposition, or using an alternative resource assignment for a given task, recommend changing some temporal orderings of tasks, or suggest other edits to any of the objects used by HICAP to define plans. However, in the military task that we have studied, the only suggestions recorded in lessons are task substitutions.

4 Evaluation

We wanted to evaluate the hypothesis that the monitored distribution approach (e.g., as implemented in ALDS) is superior to the traditional standalone approach for lesson distribution and promoting lesson reuse. For HICAP/ALDS, this hypothesis requires evaluating the plans created by operational users who use the two lesson distribution approaches in repeated planning tasks. Dependent variables would include agreed-upon measures of plan quality, which depend on the planning domain. Unfortunately, HICAP/ALDS has not yet been scheduled for testing in a military training exercise, which prevents us from working with operational planners. Therefore, we instead performed an evaluation using simulated users on a simulated NEO domain. Sophisticated full-scale NEO simulators do not yet exist. Therefore, we constructed our own plan evaluator for a simulated NEO domain (Section 4.1). This allowed us to evaluate HICAP/ALDS's plan authoring and lesson distribution capability for an entire plan, rather than be limited to an evaluation on a single task decomposition task [Muñoz-Avila *et al.*, 1999].

It's difficult to *simulate* how a user might benefit from a standalone lesson dissemination tool. Therefore, we instead compared plan generation when using ALDS vs. not using it (Section 5.2), where our revised hypothesis is that *using lessons will improve plan quality*. This central hypothesis to LLPs, although simple, has *not* been previously investigated for lessons learned systems, and thus is appropriate for an initial evaluation focus.

4.1 Methodology

The plans authored by HICAP concerned performing a rescue mission where troops are grouped and move between an initial location (the assembly point) and the NEO site (where the evacuees are located), followed by evacuee re-location to a safe haven. A total of 81 possible routes and 4 means of transportation were encoded. In addition, other conditions were determined during planning such as communication with DOD personnel and the method for processing evacuees. HICAP's plans had 18 steps, its knowledge base included 6 operators, 22 methods and 51 cases. We randomly selected 100 initial plan states (12 independent variables) and produced plans for each state with the simulated user interacting with HICAP. This user assigned, through task decomposition, an additional 18 variables (with one to up to four value each) for each plan, which averaged HICAP about 40 seconds to generate. The same set of initial states to produce plans in HICAP were used (to guide task decomposition) both with and without lessons. Each of the two sets of 100 plans (i.e., one set obtained using lessons, and the second set obtained without using lessons) authored by HICAP were input to the evaluator (Section 4.2). Due to the non-deterministic behavior of the evaluator, we executed each plan ten times.

The version of HICAP used in this paper is deterministic; given a state and a top-level goal (i.e., perform a NEO), it will always generate the same plan. A simulated user interacts with HICAP choosing task decompositions to generate a plan, using the process shown in Figure 3. In NaCoDAE/HTN conversations, it always answers the top-ranking displayed question for which it has an answer, and it answered questions until either none remained unanswered or until one of the solutions exceeded a retrieval threshold, which we set to 50%.

We selected 11 lessons for our experiment, representing a subset of approximately 56 (obviously) NEO-related lessons from the Active Navy lesson repository (containing 5120 lessons) from the November 2000 copy of the unclassified Navy Lessons Learned System. These were selected according to their relevance to NEOs and their clarity, so that we could recognize their relation to the plans authored using HICAP. For example, one lesson was defined as:

Conditions: (<q,a> pairs)

Does medical inventory correspond to standard or standard minus ? Yes

Is the climate tropical? Yes

Task: Standard Medical Inventory

Suggested Substitute Task: Add to medical inventory

4.2 Plan evaluation

We built a stochastic evaluator for NEO plans that takes into account general knowledge of the NEO domain and computes the performance measures (described below). This evaluator is not a simulator because it does not use specific distributions for each type of event, but simply computes within a uniform variability what are the expected consequences of some choices in building a plan as in a causal chain of events that have different influences on each of the dependent variables. We built the evaluator and the HICAP knowledge base for mock NEOs where we had real lessons that were applicable.

We defined plan quality based on official measures of NEOs, which are planning domain dependent. These measures are defined in the Universal Naval Task List [UNTL, 1996]

under measures of performance suggested for Joint and Naval tasks. These measures primarily concern execution duration and casualty rates. To avoid a redundant evaluation, we have selected one measure for total duration of the operation, one for duration until evacuees receive medical assistance, and the percentage of casualties among evacuees, friendly forces, and enemies. These summarize the most important aspects suggested in the UNTL.

We defined bounds for variables based on actual NEOs. For example, we limited the percentage of casualties occurred after a severe enemy attack takes place. Enemy attacks will only be possible in two planning segments (out of a total of five segments) and their likelihood increases when users choose land transportation and decreases when weather is troublesome. There is a small chance of a crash when helicopters are used that increases if the weather is not favorable; the resulting number of casualties is proportional to the number of passengers in each aircraft. A long planning segment flown by helicopter will have added the time and risks associated to the required refueling (e.g., Siegel, 1991).

Table 1. Experimental results with the 100 plans.

	Without lessons	With lessons	% Reduction with lessons
mean duration	39h50	32h48	18
s.d.	16h51	16h12	-
mean duration until medical asst.	29h37	24h13	18
s.d.	11h13	10h26	-
mean % casualties: to evacuees	11.48	8.69	24
to friendly forces	9.41	6.57	30
to enemies	3.08	3.14	(2)

4.3 Results

As summarized in Table 1, ALDS using lessons substantially improved the first four of five performance variables. A brief examination of the results (i.e., the first run for each of the 100 plans), using a standard student's t test, revealed significant differences for both overall duration ($p>0.1$, $t=1.60$, $df=99$) and duration until medical assistance ($p>0.1$, $t=1.39$). All lessons were used in generated plans, and an average of approximately 3 lessons were used per plan.

The significance of an overall reduction of 24% in the percentage of casualties among evacuees can be estimated in each plan based on the parameter number of evacuees (i.e., dozens, hundreds, thousands). Considering that, respectively, plans with dozens would have at least 40 evacuees, hundreds would have 300, and thousands, 3000; the measure percentage translates into an estimated number of casualties of 98 (plans without lessons) that suffers a reduction of an estimated 36 casualties in plans with lessons, where the estimated number of casualties is 62.

These results suggest that the monitored distribution approach can potentially generate better plans for realistic problem domains (e.g., planning for NEO operations). However, the experimental conditions were designed so that lessons were available for a reasonable percentage of the generated plans, and thus could be prompted to the simulated HICAP user so that, when applied, they could improve plan quality (with high probability). Nonetheless, we expect that similar improvements

may yield benefits in plans for domains where safety issues and speed are paramount to success.

Much as how the characteristics of datasets can be varied to determine when certain learning algorithms can be expected to perform well (e.g., Aha, 1992), we plan to characterize the set of experimental conditions for which ALDS can use lessons to significantly improve plan evaluation performance measures.

5 Discussion

This paper proposes a technology (i.e., case-based reasoning) solution to part of a knowledge management (KM) problem (i.e., managing lessons learned). However, KM problems typically require challenging organizational dynamics issues, and these require precedence in the context of bridging the lesson distribution gap. Thus, monitored distribution can at most play only one part of a much larger solution.

Our evaluation of the ALDS demonstrates how monitored distribution, when embedded in a decision-making (i.e., planning) process, can improve the results of that process. Although we used simulated users in our experiments to reduce human biases during the evaluation, we stress that this is a mixed-initiative approach in which humans interact with HICAP to generate plans. Perhaps the most unique aspect of ALDS is that it allows users to execute a lesson's suggestion (i.e., here, a task substitution), rather than limit them to simply browsing the suggestion.

HICAP's NaCoDAE/HTN module manipulates *cases* that represent task decompositions corresponding to either standard operating procedures or decompositions that were derived from decision making during training exercises and actual operations. In contrast, ALDS manipulates *lessons* that capture experiences that, if reused, can significantly impact the performance of subsequent plans. Unlike cases, lessons are not conceptually limited to representing task decompositions, but can be used to apply edits to *any* of HICAP's objects (e.g., resource assignments, resources, task durations).

Although several workshops (e.g., organized by the Department of Energy, the European Space Agency, the Joint Warfighting Center, and each branch of the armed services) have now taken place on the topic of lessons learned, few efforts on lessons learned systems have examined the potential utility of AI (e.g., Vandeville and Shaikh [1999] briefly mention using fuzzy set theory to analyze elicited lessons), and there is a lack of closely related work to monitored distribution. However, one recent workshop brought attention to this area from an AI perspective [Aha and Weber, 2000], and a few of its contributors touched on issues related to proactive lesson distribution. For example, Leake *et al.*'s [2000] CALVIN system implements a task-oriented LLP that collects lessons about research topics and research results with an active distribution sub-process. Like ALDS, CALVIN prompts users with suggestions (i.e., alternative WWW pages to browse) that can be immediately executed. However, while CALVIN focuses on a diagnosis task, ALDS operates in the context of a synthesis task (i.e., planning), and can update any of the planning scenario's objects. Like both of these systems, Watson [2000] also describes a case retrieval system, in this case for extending Cool Air to distribute trouble tickets. However, Cool Air does not operate in a mixed-initiative setting. Some KM approaches [Reimer *et al.*, 2000; Abecker *et al.*, 2000] also target distribution in context of general organizational knowledge, but without specifying a structured format indexed by its applicability like lessons.

Several limitations exist concerning our approach and its implementation in ALDS. For example, lesson collection in our approach was ignored, and was performed manually for this experiment. We are currently investigating interactive elicitation approaches for lesson collection, as well as text mining approaches, to populate ALDS's lesson repository.

6 Conclusion

We identified a problem with distributing lessons, called the *lesson distribution gap*, that is crucial to many lessons learned organizations. To address this problem, we introduced an approach called *monitored distribution*, which is characterized by a tight integration with a decision support tool that manages processes that the lessons can potentially improve. We implemented this approach in ALDS, a case-based reasoning system, and evaluated its capability in the context of a module for HICAP, a plan authoring tool. Our experiments with a simulated military planning domain (i.e., for noncombatant evacuation operations (NEOs)) showed that, by using lessons, monitored distribution can help to significantly improve plan performance measures. In summary, we demonstrated a technology that brings lessons to the attention of users when and where they are needed and applicable.

In future work, we intend to compare the monitored distribution approach vs. traditional keyword search tools for lessons in the context of user experiments. We also intend to demonstrate that monitored distribution is not restricted to planning for NEOs, nor for planning in general. For example, we are currently working with the Joint Warfighting Center to demonstrate the utility of HICAP/ALDS for a crisis action planning scenario.

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