Planning in a Multi-Agent Environment: Theory and Practice

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Abstract

We give the theoretical foundations and empirical evaluation of a planning agent, `shop`, performing *HTN* planning in a multi-agent environment. `shop` is based on *A-SHOP*, an agentized version of the original *SHOP HTN* planning algorithm, and is integrated in the *IMPACT* multi-agent environment. We ran several experiments involving accessing various distributed, heterogeneous information sources, based on simplified versions of noncombatant evacuation operations, NEO's. As a result, we noticed that in such realistic settings the time spent on communication (including network time) is orders of magnitude higher than the actual inference process. This has important consequences for optimizations of such planners. Our main results are: (1) using NEO's as new, more realistic benchmarks for planners acting in an agent environment, and (2) a memoization mechanism implemented on top of `shop`, which improves the overall performance a lot.

1. Introduction

Planning a course of action is difficult, especially for large military organizations (e.g., the U.S. Navy) that have their available assets distributed world-wide. Formulating a plan in this context requires accessing remote, heterogeneous information sources. For example, when planning for a *Noncombatant evacuation operation*, denoted by NEO, military commanders must access several information sources including: assets available in the zone of operations, Intelligence assessment about potential hostiles, weather conditions and so forth.

A-SHOP is an *HTN* planning algorithm for planning in a multi-agent environment. *A-SHOP* can interact with external information sources, frequently heterogeneous and not necessarily centralized, via the *IMPACT* multi-agent environment. The *IMPACT* project (see (ESP99; SBD$^+$00) and `http://www.cs.umd.edu/projects/impact/`) aims at developing a powerful and flexible, yet easy to handle framework for the interoperability of distributed heterogeneous sources of information.

In previous work we described the definition of the *A-SHOP* planning algorithm, an agentized version of *SHOP* that runs in the *IMPACT* environment and formulated the conditions needed for *A-SHOP* to be sound and complete (NN02).

In this paper we will focus on the actual implementation of *A-SHOP* following the principles stated in our previous work and experiments we did on a transportation domain for NEO operations. Our analysis of the initial runs of *A-SHOP* revealed that most of the running time was spent on communication between the *IMPACT* agents and accessing the information sources. Compared to that, the actual inferencing time in *A-SHOP* was very small. Furthermore, we observed that frequently the same *IMPACT* query was performed several times. To solve this problem we implemented a memoization mechanism to avoid repeating the same *IMPACT* queries. As we will show, the key for this mechanism to work is that the *A-SHOP* algorithm performs a planning technique called ordered task decomposition. As a result, *A-SHOP* maintains partial information about the state of the world. Experiments performed show that the memoization mechanism results in a significant reduction of the running time in *A-SHOP*. This reduction depends on the overall network time spent to access the information sources: the higher this network time, the higher is the gain obtained by our memoization technique.

This paper is organized as follows. The next section describes the Noncombatant evacuation operations (NEO's) planning domain, which partly motivated our approach.

In Section 3 we introduce *IMPACT*, define *A-SHOP* and the results establishing the soundness and completeness of *A-SHOP*. Section 4 describes the actual implementation of *A-SHOP*. Section 5 describes the memoization mechanism and its dependence on the Ordered Task Decomposition planning technique. In Section 6 we describe several experiments with *A-SHOP* for logistics NEO problems. Finally, we discuss related work in Section 7 and conclude with Section 8.

2. Planning Noncombatant Evacuation Operations (NEO's)

Noncombatant evacuation operations are conducted to assist the U.S.A. Department of State (*DOS*) with evacuating noncombatants, nonessential military personnel, selected host-nation citizens, and third country nationals whose lives are in danger from locations in a host foreign nation to an appropriate safe haven. They usually involve the swift insertion of a force, temporary

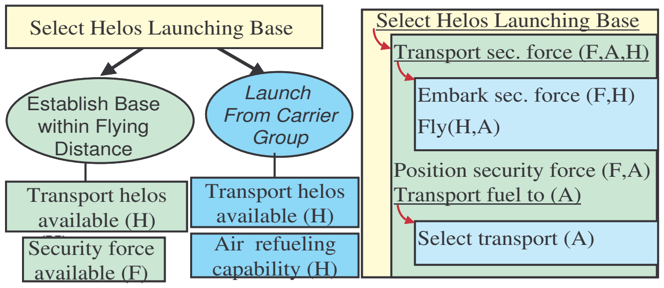
Select Helos Launching Base
Establish Base within Flying Distance
Launch From Carrier Group
Transport helos available (H)
Security force available (F)
Transport helos available (H)
Air refueling capability (H)
Select Helos Launching Base
Transport sec. force (F,A,H)
Embark sec. force (F,H)
Fly(H,A)
Position security force (F,A)
Transport fuel to (A)
Select transport (A)

Figure 1: NEO transportation example.

occupation of an objective (e.g., an embassy), and a planned withdrawal after mission completion. NEO's are often planned and executed by a Joint Task Force (*JTF*), a hierarchical multi-service military organization, and conducted under an American Ambassador's authority.

The decision making process for a NEO is conducted at three increasingly-specific levels: *strategic*, *operational* and *tactical*. The strategic level involves global and political considerations such as whether to perform the NEO. The operational level involves considerations such as determining the size and composition of its execution force. The tactical level is the concrete level, which assigns specific resources to specific tasks. Thus, this domain is particularly suitable for a hierarchical (*HTN*) planning approach.

JTF commanders plan NEO's by gathering information from multiple sources. For example, in preparation for *Operation Eastern Exit* (Mogadishu, Somalia, 1991), commanders accessed Intelligence Satellite Photographs from NIMA (National Imagery and Mapping Agency), intelligence assessment information from the *CIA*, the Emergency Action Plan (*EAP*) from the US Embassy in Mogadishu, among others (Sie91). Any automated system planning in this domain must be able to access these multiple distributed information sources.

3. Planning with Remote, Heterogeneous Information Sources

In this section we review results obtained in (NN02). After giving a brief overview on *SHOP* and *IMPACT*, we state the main results of (NN02).

SHOP

Rather than giving a detailed description of the kind of *HTN* planning used by *SHOP* ((NCLMA99)), we consider the following example.

In order to do planning in a given planning domain, *SHOP* needs to be given knowledge about that domain. *SHOP*'s knowledge base contains *operators* and *methods*. Each operator is a description of what needs to be done to accomplish some primitive task, and each method is a prescription for how to decompose some complex task into a totally ordered sequence of subtasks, along with various restrictions that must be satisfied in order for the method to be applicable.

Given the next task to accomplish, *SHOP* chooses an applicable method, instantiates it to decompose the task into subtasks, and then chooses and instantiates other methods to decompose the subtasks even further. If the constraints on the subtasks prevent the plan from being feasible, *SHOP* will backtrack and try other methods.

As an example, Figure 1 shows two methods for the task of *selecting a helicopter launching base*: *establishing the base within flying distance*, and *launch from carrier battle group* (i.e., use the carrier as the helicopter launching base). Note that each method's preconditions are not used to create subgoals (as would be done in action-based planning). Rather, they are used to determine whether or not the method is applicable. *Establishing the base within flying distance* requires to have transport helicopters and a security force available. Launching from carrier battle group also requires to have helicopters available and those helicopters have to have air refuelling capability (which wasn't necessary in the first method because the helicopters are within flying distance).

If the method *establishing base within flying distance method* is selected, the select helicopter launching base is decomposed into three subtasks: transport security force (F) using the helicopters (H) to the selected launching base (A), position the security force in the base, and transport the fuel to the base. Some of these tasks, such as transporting the security force, can be further decomposed. Others such as *position security force* cannot. The former are called *compound* tasks, the latter *primitive* tasks.

IMPACT

To get a bird's eye view of *IMPACT*, here are the most important features:

Actions: Each *IMPACT* agent has certain *actions* available. Agents act in their environment according to their *agent program* and a well defined *semantics* determining which of the actions the agent should execute.

Legacy Code: *IMPACT* Agents are built on top of arbitrary software code (*Legacy Data*).

Agentization: A methodology for transforming legacy code into an *agent* has been developed.

For example, in many applications a `math` agent is needed. This agent is able to do mathematical calculations shipped to it by other agents. For example it can determine the time it takes for a particular vehicle to get from one location to another. Another example is a `monitoring` agent, that keeps track of distances between two given points and the authorized range or capacity of certain vehicles. These information can be stored in several databases.

The Code Call Machinery To perform logical reasoning on top of third party data structures (which are part of the agent's state) and code, the agent must have a language within which it can reason about the agent state. We therefore introduce the concept of a *code call atom*, which is the basic syntactic object used to access multiple heterogeneous data sources.

A code call executes an *API* function and returns as output a set of objects of the appropriate output type. Going back to our agent introduced above, $\mathtt{monitoring}$ may be able to execute the cc $\mathtt{monitoring}: \mathit{distance}(\mathtt{locFrom}, \mathtt{locTo})$. The $\mathtt{math}$ agent may want to execute the following code call: $\mathtt{math}: \mathit{computeTime}(\mathtt{cargoPlane}, \mathtt{locFrom}, \mathtt{locTo})$.

What we really need to know is if the result of evaluating such code calls is contained in a certain set or not. To do this, we introduce code call atoms. These are *logical atoms* that are layered on top of code calls. They are defined through the following inductive definition.

Definition 1 (Code Call Atoms (in($\mathtt{X}, \mathtt{cc}$))) *If* $\mathtt{cc}$ *is a code call, and* $\mathtt{X}$ *is either a variable symbol, or an object of the output type of* $\mathtt{cc}$*, then* **in**$(\mathtt{X}, \mathtt{cc})$ *and* **not_in**$(\mathtt{X}, \mathtt{cc})$ *are* code call atoms. **not_in**$(\mathtt{X}, \mathtt{cc})$ *succeeds if X is **not** in the set of objects returned by the code call cc.*

Code call atoms, when evaluated, return boolean values, and thus may be thought of as special types of logical atoms. Intuitively, a code call atom of the form **in**$(\mathtt{X}, \mathtt{cc})$ succeeds if $\mathtt{X}$ can be set to a pointer to one of the objects in the set of objects returned by executing the code call.

As an example, the following code call atom tells us that the particular plane "$f22$" is available as a cargo plane at *ISB1*: **in**$(f22, \mathtt{transportAuthority}: \mathit{cargoPlane}(\mathtt{ISB1}))$

Often, the results of evaluating code calls give us back certain values that we can compare. Based on such comparisons, certain actions might be fired or not. To this end, we need to define *code call conditions*. Intuitively, a code call condition is a conjunction of code call atoms, equalities, and inequalities. Equalities, and inequalities can be seen as additional syntax that "links" together variables occurring in the atomic code calls.

Definition 2 (Code Call Conditions (ccc))

1. *Every code call atom is a code call condition.*
2. *If* $\mathtt{s}, \mathtt{t}$ *are either variables or objects, then* $\mathtt{s} = \mathtt{t}$ *is a code call condition.*
3. *If* $\mathtt{s}, \mathtt{t}$ *are either integer/real valued objects, or are variables over the integers/reals, then* $\mathtt{s} < \mathtt{t}, \mathtt{s} > \mathtt{t}, \mathtt{s} \geq \mathtt{t}, \mathtt{s} \leq \mathtt{t}$ *are code call conditions.*
4. *If* χ_1, χ_2 *are code call conditions, then* $\chi_1 \,\&\, \chi_2$ *is a code call condition.*

A code call condition satisfying any of the first three criteria above is an atomic *code call condition.*

IMPACTING SHOP

A comparison between *IMPACT*'s actions and *SHOP*'s methods shows that *IMPACT* actions correspond to fully instantiated methods, i.e. no subtasks. While *SHOP*'s methods and operators are based on *STRIPS*, the first step is to modify the atoms in *SHOP*'s preconditions and effects, so that *SHOP*'s preconditions will be evaluated by *IMPACT*'s code call mechanism and the effects will change the state of the *IMPACT* agents. This is a fundamental change in the representation of *SHOP*. In particular, it requires replacing *SHOP*'s methods and operators with *agentized* methods and operators. These are defined as follows.

Definition 3 (Agentized Meth.: (AgentMeth $h \, \chi \, \mathbf{t}$)) *An* agentized method *is an expression (***AgentMeth** $h \, \chi \, \mathbf{t}$*) where* h *(the method's* head*) is a compound task,* χ *(the method's* preconditions*) is a code call condition and* $\mathbf{t}$ *is a totally ordered list of subtasks, called the* task list.

The primary difference between definition of an agentized method and the definition of a method in *SHOP* is as follows. In *SHOP*, preconditions were logical atoms, and *SHOP* would infer these preconditions from its current state of the world using Horn-clause inference. In contrast, the preconditions in an agentized method are *IMPACT*'s code call conditions rather than logical atoms, and *A-SHOP* (the agentized version of *SHOP* defined in the next section) does not use Horn-clause inference to establish these preconditions but instead simply invokes those code calls, which are calls to other agents (which may be Horn-clause theorem provers or may instead be something entirely different).

Definition 4 (Agentized Op.: (AgentOp $h \, \chi_{add} \, \chi_{del}$)) *An* agentized operator *is an expression (***AgentOp** $h \, \chi_{add} \, \chi_{del}$*), where* h *(the* head*) is a primitive task and* χ_{add} *and* χ_{del} *are lists of code calls (called the* add- *and* delete-lists*). The set of variables in the tasks in* χ_{add} *and* χ_{del} *is a subset of the set of variables in* h*.*

The Algorithm

```
procedure A-SHOP($\mathbf{t}, \mathcal{D}$)
   1. if $\mathbf{t} = nil$ then return $nil$
   2. $t :=$ the first task in $\mathbf{t}$; $R :=$ the remaining tasks
   3. if $t$ is primitive and a simple plan for $t$ exists then
   4.    $q := simplePlan(t)$
   5.    return $concatenate(q, A\text{-}SHOP(R, \mathcal{D}))$
   6. else if $t$ is non-prim. $\wedge$ there is a reduction of $t$
then
   7.    nondeterministically choose a reduction:
        Nondeterministically choose an agentized method,
          (AgentMeth $h \, \chi \, t$), with $\mu$ the most general
          unifier of $h$ and $t$ and substitution $\theta$ s.t.
         $\chi\mu\theta$ is ground and holds in IMPACT's state $\mathcal{O}$.
   8.    return $A\text{-}SHOP(concatenate(t\mu\theta, R), \mathcal{D})$
   9. else return FAIL
  10. end if
end A-SHOP

procedure simplePlan($t$)
  11. nondeterministically choose agent. operator
        $\mathsf{Op} =$ (AgentOp $h \, \chi_{add} \, \chi_{del}$) with $\nu$ the most
        general unifier of $h$ and $t$ s.t. $h$ is ground
  12. monitoring : $apply(\mathsf{Op}\,\nu)$
  13. return $\mathsf{Op}\,\nu$
end A-SHOP
```

Figure 2: *A-SHOP*, the agentized version of *SHOP*.

The *A-SHOP* algorithm is now an easy adaptation of the original *SHOP* algorithm. Unlike *SHOP* (which would apply an operator by directly inserting and deleting atoms from an internally-maintained state of the world), *A-SHOP* needs to reason about how the code calls in an operator will affect the states of other agents. One might think the simplest way to do this would be simply to tell these agents to execute the code calls and then observe the results, but this would not work correctly. Once the planning process has ended successfully, *A-SHOP* will return a plan whose operators can be applied to modify the states of the other *IMPACT* agents—but *A-SHOP* should not change the states of those agents during its planning process because this would prevent *A-SHOP* from backtracking and trying other operators.

Thus in Step 12, *SHOP* does not issue code calls to the other agents directly, but instead communicates them to a monitoring agent. The monitoring agent keeps track of all operators that are supposed to be applied, without actually modifying the states of the other *IMPACT* agents. When *A-SHOP* queries for a code call $cc = \mathcal{S} : f(\mathtt{d}_1, \ldots, \mathtt{d}_n)$ in χ to evaluate a method's precondition (Step 7), the monitoring agent examines if *cc* has been affected by the intended modifications of the operators and, if so, it evaluates *cc*. If *cc* is not affected by application of operations, *IMPACT* evaluates *cc* (i.e., by accessing $\mathcal{S}$). The list of operators maintained by the monitoring agent is reset whenever a planning process begins. The *apply* function applies the operators and creates copies of the state of the world. Depending on the underlying software code, these changes might be easily revertible or not. In the latter case, the monitoring agent has to keep track of the old state of the world.

Finite Evaluability of ccc's and Completeness of ASHOP

We have introduced syntactic conditions, similar to *safety* (and consequently called *strong safety*) in classical databases, to ensure evaluability and termination of ccc's (see (ESR00; SBD$^+$00)).

Theorem 1 (Soundness, Completeness) *Let $\mathcal{O}$ be a state and $\mathcal{D}$ be a collection of agentized methods and operators. If all the preconditions in the agentized methods and add and delete-lists in the agentized operators are strongly safe wrt. the respective variables in the heads, then A-SHOP is correct and complete.*

4. ASHOP: Implementation

Each cycle in the *A-SHOP* algorithm consist of three phases (see lines 3 and 7 of Figure):

1. *Selection Phase*: Selecting a candidate agentized method or operator to reduce a task.
2. *Evaluation Phase*: Evaluating the applicability of the chosen agentized method or operator.
3. *Reduction Phase*: Performing the agentized method or operator.

To accomplish these phases we have implemented 3 *IMPACT* agents which perform pieces of these phases:

ashop: This is the agent that all *IMPACT* agents communicate with for generating a plan. It receives as input a problem and outputs a solution plan. The *A-SHOP* agent also performs the Selection Phase and the evaluation phase for the situation in which an operator is chosen. The operator is then send to the Monitor Agent, to perform a *virtual execution* of it. If the selection of a method is made, the *A-SHOP* agent sends a message to the Preconditions Agent with the code-call condition of the selected method.

preconditions: Receives a code-call condition and evaluates each code-call by sending it to the Monitoring Agent.

monitoring: The monitor agent has two functions: firstly, it receives a operator and performs a virtual execution of it. Secondly, it receives code-calls and evaluates them. We explain both of these operations in detail below as they are closely inter-related.

One of the main issues we are confronted with during the implementation is how to cope with the *execution* of agentized operators. In classical AI planning, where the state is centralized, executing an operator is a matter of simply making the changes to the state indicated by the operator and keeping track of those changes in an stack; if backtracking occurs, the stack is used to restore to the previous state.

This approach is not working in a multi-agent environment, where the state is distributed among several information sources. Firstly, remote information sources might not be able to backtrack to a previous state. Secondly, even if backtracking was possible, performing such an operation may be costly. Thirdly, executing an operation may make resources unavailable temporarily for other agents and if backtracking takes place, these resources could have been used. For example, an operator may reserve a *recon* plane but a later operator trying to provide flight escort to the *recon* plane might not succeed. In this case the original *recon* plane should have not been reserved in the first place.

The Monitoring Agent overcomes these problems by keeping track of each operator execution without accessing the corresponding information sources to request an execution of the operation. For this reason we refer to this as a *virtual operator execution.* Since monitoring keeps track of the changes in the states of the remote information sources, the preconditions sends the code-calls to the monitoring. monitoring makes the code-call to the corresponding information source and then checks if the answer is affected by the previously virtually executed operators before sending its answer to the preconditions.

5. Memoization in ASHOP

While our implementation secures that the produced plans are consistent, the resulting running time was large compared to the inferencing time (we will describe the experiments later). Our experiments show that the bulk of the planning time has been spent in accessing the remote information sources. Further analysis revealed that the same code-calls were repeatedly being executed during the planning process. Our solution was to implement a cache mechanism to avoid repeated evaluations of the same code call in *IMPACT*.

Again this issue marked a difference from classical AI planning approaches. In *SHOP*, for example, we use a hash table to quickly check the validity of a condition in the current state. Other planning systems use more sophisticated data structures to reduce the time for evaluating a condition in the current state. For example, *TLPlan*, the winner of the 2000 AI planning competition, uses a bit map that allows checking conditions in almost constant time (Bac01).

Obviously none of these techniques would be useful here since the information sources are remote and *A-SHOP* has no control over how data is stored there and how it is updated. However, implementing a memoization mechanism turned out to be adequate for *A-SHOP* for two reasons: Firstly, *A-SHOP* performs *Ordered Task Decomposition*. Secondly, all access to the information sources is canalized through monitoring.

The fact that access to the information sources is canalized through monitoring makes this agent the natural place for maintaining the updated partial state of the world. As a result, we modified monitoring:

- When it receives a code-call from preconditions, the monitoring will first check if the code-call can be answered based on previous code-calls and the modifications indicated by the virtually executed operators. Only if it is not possible to answer this code call, the remote information source is accessed via the *IMPACT* code-call evaluation mechanism.
- After, receiving the answer from *IMPACT* for the evaluation of the code-call, monitoring records this answer.

In the example of the *recon* plane, after the first operator reserving the *recon* plane is virtually executed, monitoring knows that there are no more *recon* planes available. Thus, as it receives the code-call enquiring about the availability of *recon* planes it will answer that this code-call cannot be satisfied without having to access the corresponding remote information source via *IMPACT*. As will be shown next, these changes resulted in a reduction of the running time.

6. Empirical Evaluation

The test domain is a simple transportation planning for a NEO (MAAN$^+$01). Its plans involve performing a rescue mission where troops are grouped and transported between an initial location (the assembly point) and the NEO site (where the evacuees are located). After the troops arrived at the NEO site, evacuees are re-located to a safe haven.

Planning involves selecting possible pre-defined routes, consisting of four or more segments each. The planner must also choose a transportation mode for each segment. In addition, other conditions were determined during planning such as whether communication exists with *State Department personnel* and the type of evacuee registration process. *A-SHOP*'s knowledge base included six agentized operators and 22 agentized methods. There were four *IMPACT* information sources available:

- Transport Authority: Maintains information about the transportation assets available at different locations.
- Weather Authority: Maintains information about the weather conditions at the different locations.
- Airport Authority: Maintains information about availability and conditions of airports at different locations.
- Math Agent: math evaluates arithmetic expressions. typical evaluations include the subtract a certain number of assets use for an operation and update time delays.

The top level task for each problem in this experiment was the following: to perform a troop insertion and evacuees extraction plan. This top level task is decomposed into several subtasks, one for each segment in the route that the troops must cover (these segments are pre-determined as part of the problem description). Within each segment, *A-SHOP* must plan for the means of transportation (planes, helicopters, vehicles etc.) to be used and select a route for that segment. The selection of the means of transportation depends on their availability for that segment, the weather conditions, and, in the case of airplanes, on the availability and conditions of airports. The selection of the route depends on the transportation vehicle used and may lead to backtracking. For example, the choice of ground transportation assets needs to be revised if no roads are available or they are blocked, or too risky to take.

We ran our experiments on 30 problems of increasing size. The first five problems had four segments passing over five locations (including a particular location known as the Intermediate Staging Base *ISB*), the next five problems had five segments passing over six locations (two *ISB*'s), and so forth until the Problems 26–30 which had nine segments passing over 10 locations (five *ISB*'s).

We ran shop in two modes: with and without the memoization mechanism and measured for each mode two variables: *inferencing time* and *total time*. The inferencing time includes the time spent in the three agents implementing the *A-SHOP* algorithm. Thus, the difference between the total time and the running time indicates the sum of the communication time needed by *IMPACT* to access the remote information sources and of the time needed by the information sources to compute the answers to the queries.

Figure 3 shows the results of the experiments. Not surprisingly the inferencing times with and without memoization are almost identical. More interesting is the fact that the inferencing time is only a fraction of the overall running time. In addition, the use of the memoization mechanism results in a decrease in the running time of more than 30%.

7. Related Work

Most AI planning systems are unable to evaluate numeric conditions at all. A few can evaluate numeric conditions using attached procedures (e.g., *SIPE* (Wil88), *O-Plan* (CT91), *TLPlan* (BK00) and *SHOP* (NCLMA99)), but the lack of a formal semantics for

Figure 3: Results of the experiments.

these attached procedures makes it more difficult to guarantee soundness and completeness. Integer Programming (IP) models appear to have excellent potential as a uniform formalism for reasoning about complex numeric and symbolic constraints during planning, and some work is already being done on the use of IP for reasoning about resources (Köh98; KW99; WW99). However, that work is still work in progress, and a number of fundamental problems still remain to be solved.

Approaches for planning with external information sources typically have in common that the information extracted from the external information sources is introduced in the planning system through built-in predicates (EWD$^+$92; GEW94; Kno96; FW97). For example, a modified version of *UCPOP* uses *information gathering goals* to extract information from the external information sources (Kno96). The information gathering goals are used as preconditions of the operators. The primary difficulty with this approach is that since it is not clear what the semantic of the built-in predicates is, this makes it difficult to guarantee soundness and completeness.

8. Conclusion

The original motivation of our work was to make *HTN* planning available in a multi-agent environment. This is beneficial for both, planners (they gain access to distributed and heterogenous information sources for free and can ship various tasks to other agents) as well as agent systems (which usually do not have available planning components that are highly sophisticated and efficient).

After developing the theory and implementing it, we ran experiments on a simplified version of the NEO domain, where data needed for the planning process is distributed and highly heterogenous. In such a situation, data changes dynamically, eg. weather conditions or available resources. Thus the available data can not be stored locally, because of the sheer amount and the dynamic changes in the database.

Our experiments revealed clearly that most of the time is spent on communication with the information sources and therefore network time. Thus improving the actual planning algorithm (as done by most planners that assume all info is there locally) does not pay off: the amount gained is orders of magnitude less than the overall time. We really need caching mechanisms, to avoid computing the same results over and over again. In the extreme case, when caching is just storing everything locally, we would end up with our original local planner. This is not feasible because of the amount of data involved and the fact that it changes dynamically. The other extreme is not to do any caching at all. Our memoization technique seems to be a good compromise between these two extremes. The decrease in time we are getting depends on the overall network time spent to access the information sources: the higher this network time, the higher is the gain obtained by our memoization technique. Consequently our experiments showed an overall gain ranging from 20%-40%.

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