


# Aplib: Tactical Programming of Intelligent Agents

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Abstract: This paper presents `aplib`, a Java library for programming intelligent agents, featuring BDI and multi agency, but adding on top of it a novel layer of tactical programming inspired by the domain of theorem proving. `Aplib` is also implemented in such a way to provide the fluency of a Domain Specific Language (DSL). Compared to dedicated BDI agent programming languages such as JASON, 2APL, or GOAL, `aplib`'s embedded DSL approach does mean that `aplib` programmers will still be limited by Java syntax, but on other hand they get all the advantages that Java programmers get: rich language features (object orientation, static type checking,  $\lambda$ -expression, libraries, etc), a whole array of development tools, integration with other technologies, large community, etc.

## 1 INTRODUCTION

Software agents are generally considered as a different type of programs than e.g. procedures and objects as they are naturally autonomous, reactive as well as pro-active, and 'social' (they interact with each other) (Wooldridge and Jennings, 1995; Meyer, 2008). As such, they are considered as highly suitable building blocks to build complex software systems that require multiple and decentralized loci of control (Jennings, 2001). Applications of software agents include computer games, health care, traffic control system (Jennings et al., 1998), smart electrical power grid control (Merabet et al., 2014), and manufacturing control system (Leitão, 2009).

In a stronger concept of agency (Wooldridge and Jennings, 1995), agents can also possess artificial intelligence. The most popular type of intelligent agents is probably that of the BDI (Belief-Desire-Intent) family (Herzig et al., 2017). Such an agent maintains a set of human-inspired mental states, such as belief, desire, and intention, and is able to reason over these states when deciding its actions. While adding AI would greatly enhance agents, it is not something that we get for free as the AI would need some programming in the first place. In the case of BDI agents, someone would need to produce the set of inference rules that control their actions. There are indeed programming languages to program BDI agents, e.g. JASON (Bordini et al., 2007), 2APL (Dastani, 2008), GOAL (Hin-


driks, 2018), JACK (Winikoff, 2005), FATIMA (Dias et al., 2014), and PROFETA (Fichera et al., 2017), that allow the rules to be declaratively formulated, but this does not necessarily mean that it is easy for agent programmers to develop these rules, especially if the problem to solve is complex.

This paper presents `aplib`<sup>1</sup>: a BDI agent programming framework that adds as novelty a layer of *tactical programming* over the rule based programming typical in BDI agent programming. Tactics allow agents to strategically choose and prioritize their short term plans. This is inspired by proof programming in LCF theorem provers like Coq and HOL (Delahaye, 2000; Gordon and Melham, 1993). These theorem provers come with a whole range of proof rules. However, having plenty of rules does not in itself make proving formulas easy. In fact, proving a complex goal formula often involves interactively trying out different steps, searching for the right sequence that would solve the goal. To help users, these theorem provers provide tactical combinators to compose tactics from proof rules, hence users can write proofs by sequencing tactics rather than proof rules. There is some analogy with agents, which also have to solve non-trivial goals, hence inspiring `aplib` to provide a similar tactical approach to program agents.

While tactics are good to capture bottom-up strategies to solve a goal<sup>2</sup>, sometimes it is also useful

<sup>1</sup><https://iv4xr-project.github.io/aplib/>

<sup>2</sup>With respect to the previously mentioned concept of 'tactic' in LCF theorem provers, `aplib` tactics express

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to have top-down strategies. This can be expressed by a way to break down a goal into subgoals. Aplib facilitates this through the concept of *goal structure*, that allows a goal to be hierarchically formulated from subgoals through a number of strategy combinators, e.g. to express fall backs (alternate goals if the original goal fails). While it is true that tactics and goal structures can be programmed inside BDI agents' reasoning rules, we would argue that tactical programming involves a different mental process for programmers. Aplib allows them to be programmed separately and more abstractly, rather than forcing the programmers to encode them inside reasoning rules.

Unlike JASON, 2APL, or GOAL, which offer a native/dedicated BDI agent programming, aplib offers a Domain Specific Language (DSL) to program agents, *embedded* in Java. This means that aplib programmers will program in Java, but they will get a set of APIs that give the fluent appearance of a DSL. In principle, having a native programming language is a huge benefit, but **only** if the language is mature and scalable. On the other hand, using an embedded DSL means that the programmers have direct access to all the benefit the host language, in this case Java: its expressiveness (OO, lambda expression etc), static typing, rich libraries, and wealth of development tools. These are things that JASON, 2APL, nor GOAL cannot offer. It is also worth noting that elsewhere, the rapidly growing popularity of AI and data science *libraries* like TensorFlow, NumPy, and Java-ML can be seen as evidence that developers are quite willing to sacrifice the convenience of having a native language in exchange for strength.

**Paper structure.** Section 2 first introduces some notation and concepts from OO programming that might be non-standard. Related work will be discussed later, namely in Section 7. Section 3 explains the basic concepts of aplib agents and shows examples of how to create an agent with aplib and how to write some simple tactics. The section also presents aplib's deliberation algorithm, which necessarily has to extend the standard BDI deliberation algorithm. Section 4 presents aplib's tactical programming. Section 5 discusses aplib's reasoning backend, and Section 6 presents aplib's goal structuring mechanism and also discusses budgeting as a means to control agent's commitment to goals. Finally Section 8 concludes and mentions some future work.

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bottom-up strategies, whereas LCF tactics are top-down. Aside from the directions, both concepts intend to express strategical composition of the underlying basic steps.

## 2 Preliminary

**Notation.** Since aplib is implemented in Java, most of its concepts are implemented as objects. Objects can be structured *hierarchically*. We use the notation  $u \rightarrow v$  to denote that the object  $v$  is linked from  $u$  through a reference inside  $u$  (and therefore its state is also reachable from  $u$ ). This is useful for abstraction, as sometimes it is convenient to talk about the structure  $u \rightarrow v$  in terms of its parent  $u$  while being implicit about the subobject  $v$ .

**Java functions.** Since Java 8, functions can be conveniently formulated using so-called lambda expressions. E.g. the Java expression:

$$x \rightarrow x+1$$

constructs a nameless function that takes one parameter,  $x$ , and returns the value of  $x+1$ . Aplib relies heavily on functions. Traditionally, to add behavior to an object we do that by defining a method, say  $m()$ , in the class  $C$  to which the object belongs to. But then all objects of  $C$  will have the same behavior. If we want to assign a different behavior to some of them we have to first create a subclass  $C'$  of  $C$  where we override  $m()$  with the new behavior, and then instantiate  $C'$  to obtain new objects with the new behavior. If we expect to do this often, this approach will clutter the code. Instead, in aplib we often apply a design pattern similar to the Strategy Pattern (Gamma et al., 1994), where we implement  $m$  as a field of type Function. If we have an object  $u : C$ , and we want to change the behavior of its  $m$ , we can simply assign a new function to it, as in  $u.m = x \rightarrow x+1$ . There is no overhead of having to create a subclass.

Unlike in a pure functional language like Haskell, Java functions can be either *pure* (has no side effect) or *impure/effectful*. An *effectful* function of type  $C \rightarrow D$  takes an object  $u : C$  and returns some object  $v : D$ , and may also alter the state of  $u$ .

## 3 Aplib Agency

Figure 1 illustrates the typical way aplib agents are deployed. As common with software agents, aplib agents are intended to be used in conjunction with an *environment* (the 'real environment' in Fig. 1), which is assumed to run autonomously for its own purpose. This environment can be e.g. a computer game, a simulator, a trading system, or a manufacturing system as in (Leitão, 2009). Each agent would have its own goal, which can be to simply monitor the environment, or to influence it in a certain way. Some agents may work together towards a collective goal, whereas others might be competitors. A group of agents that wish to collaborate can register to a 'communication

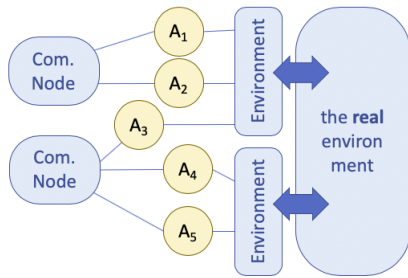


Figure 1: Typical deployment of aplib agents. In the picture,  $A_i$  are agents. "Com. nodes" allow connected agents to send messages to each other. In aplib terminology, an 'environment' is an interface to the real environment. The agents themselves will not see the distinction.

node' (see Fig. 1). Agents sharing the same node can send messages to each other (singlecast, broadcast, or role-based multicast).

Agents are assumed to have *no* direct access to the real environment's state, e.g. due to security concerns. Instead, an agent can 'sense' the environment to obtain insight on a part of its state that the agent is allowed to see. To influence the environment, the agent can send commands to the latter, from a set of available commands. The environment can also send messages to the agent, e.g. to notify it that something that might interest the agent just happened. The same facility can also be used by agents to send messages to each others. Sending messages to aplib agents is an asynchronous operation, hence the environment is not slowed (or worse: locked) when it tries to send a message to an agent. Sending a command to the environment is a synchronous operation: the sending agent halts until it gets a return value from the environment confirming if the command succeeded or failed.

**BDI with goal structure.** As typical in BDI (Belief-Desire-Intent) agency, an aplib agent has a concept of belief, desire, and intent. Its belief is simply the information it has in its own state, which includes information on what it believes to be the current state of the real environment (due to the asynchronous nature of the above described agents-environment system, this is not necessarily the same as the environment's actual state). The agent can be given a *goal structure*, defining the its desire. Unlike flat structured goal-base used e.g. in 2APL and GOAL, a goal structure is richly structured, with different nodes expressing different ways of how a goal could be achieved through its subgoals. More on this will be discussed Section 6.

Abstractly, an aplib agent is a tuple:

$$A = (s_{\rightarrow E}, \Pi, \beta)$$

where  $s$  is an object representing  $A$ 's state and  $E$  is

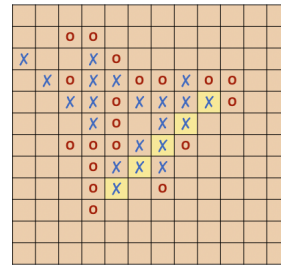


Figure 2: A GoMoku game on a  $12 \times 12$  board. Cross wins the game with a winning diagonal (yellow).

its environment. More precisely,  $E$  is an interface abstracting the real environment as depicted in Fig. 1.  $A$  does not have access to the real environment, though it can see whatever information that the real environment chooses to mirror in  $E$ . When  $A$  wants to send a command to the environment, it actually sends it to  $E$ , which under the hood will handle how it will be forwarded to the real environment.

$\Pi$  is a goal structure, e.g. it can be a set of goals that have to be achieved sequentially. Each goal has the form  $g_{\rightarrow T}$ , where  $T$  is a 'tactic' intended to solve it. When the agent decides to work on a goal  $g_{\rightarrow T}$ , it will commit to it. In BDI terms, this reflects intention: it will apply  $T$  repeatedly over multiple execution cycles until  $g$  is achieved/solved, or the agent has used up its 'budget' for  $g$ .

**Budget.** To control how long the agent should persist on pursuing its current goal, the component  $\beta$  specifies how much computing budget the agent has. Executing a tactic consumes some budget. So, this is only possible if  $\beta > 0$ . Consequently, a goal will automatically fail when  $\beta$  reaches 0. Budget plays an important role when dealing with a goal structure with multiple goals as the agent will have to decide how to divide the budget over different goals. This will be discussed later in Section 6.

**Example.** As a running example suppose we want to develop an agent to play a well known board game called *GoMoku*. The game is played on a board consisting of  $N \times N$  squares. Two players take turn to put one piece every turn, a cross for player-1, and a circle for the other. The player that manages to occupy five consecutive squares, horizontally, vertically, or diagonally, with his own pieces, wins. Fig. 2 shows an example of a GoMoku board.

Figure 3 shows how we create this agent in aplib. We call it *Crosy* (it is intended to play the role of player-1, with cross). Lines 1-7 show the relevant part of the environment the agent will use to interface with the actual GoMoku game. It has e.g. the method  $move(t, x, y)$  to place a piece of type  $t$  (cross or circle) in the square  $(x, y)$ .

```

class GoMokuEnv extends Environment {
    static String CROSS = "cross" ;
    static String CIRCLE = "circle" ;
    void move(String ptype, int x, int y) ...
    boolean crossWin() ...
    Set<Square> emptySquares() ...
}
var Π = goal("g")
. toSolve(s → s.env.crossWin())
. tactic(T) ;

var Croxy = new BasicAgent()
. withState(new AgentState())
. withEnvironment(gomEnv)
. setGoal(Π)
. budget(200)

var dumb = action("dumb").
. do_((AgentState s) → (Square sq) → {
    s.env.move(CROSS, sq.x, sq.y) ;
    return s.env.crossWin() }
)
. on_((AgentState s) → {
    var empties = s.env.emptySquares() ;
    if (empties.size()==0) return null ;
    return empties.get(rnd.nextInt(empties.size())) }
) ;

```

Figure 3: Creating an agent named Croxy to play GoMoku. Note that the code above is in Java. Aplib is not a separate programming language. Instead, it is a DSL embedded in Java. The notation  $x \rightarrow e$  in line 9 is Java lambda expression defining a function (see also Section 2), in this case a predicate defining the goal.

Lines 12-15 creates the agent. It shows that a fresh state is created and attached to the agent (line 13). Assuming gomEnv is an initialized instance of GoMokuEnv (defined in lines 1 - 7), line 14 hooks this environment to the agent. Line 15 assigns the goal  $\Pi$  to the agent, defined in lines 8-10, stating that the desired situation is where the game is won by cross (line 9). Line 10 associates the tactic  $T$  (its definition is not shown) to this goal, which the agent will use to solve the latter.

### 3.1 Action

A tactic is made of so-called actions, composed hierarchically to define a goal-solving strategy. Such composition will be discussed in Section 4. In the simple case though, a tactic is made of just a single action. An *action* is an effectful and guarded function over the agent state. The example below shows the syntax for defining an action. It defines an action with "id" as its id, and binds the action to the Java variable  $\alpha$ :

$$\text{var } \alpha = \text{action}("id"). \text{do}_-(f). \text{on}_-(q) \quad (1)$$

Above<sup>3</sup>,  $f$  is a function defining the behavior that

<sup>3</sup> Note that **action**, **do\_**, and **on\_** are not Java keywords. They are just methods. However, they are written to also implement the Fluent Interface Pattern (Fowler and Evans, 2005). It is a design pattern commonly used in embedded Domain Specific Languages (DSLs) to 'trick' the syntax restriction of the host language to allow them to be called in a sequence as if they form a sentence to improve the fluency of the DSL.

Figure 4: An action that would randomly put a cross in an empty square in a GoMoku board. As a side note, notice that we again use lambda-expressions (lines 2 and 6) to conveniently introduce functions without having to create a class.

will be invoked when the action  $\alpha$  is executed. This function is effectful and may change the agent state.

The other,  $q$ , is a pure function specifying the 'guard' for the action. Rather than using a predicate as a guard, which would be natural, we will allow  $q$  to be written as a query. More precisely, let  $\Sigma$  be the type of the agent state, we allow  $q$  to be a function of type  $\Sigma \rightarrow R$ . So, it can be inspected on a state  $s$ , to return some value of type  $R$ . We treat  $q$  as a predicate:  $\hat{q}(r, s) \stackrel{d}{=} (q(s) = r) \wedge r \neq \text{null}$ . The action  $\alpha$  is only executable if it is enabled; it is enabled on a state  $s'$  if  $\hat{q}(r, s')$  is satisfiable (there is an  $r$  that would make it true). The behavior function  $f$  has the type  $\Sigma \rightarrow R \rightarrow V$  for some type  $V$ . When the action  $\alpha$  is executed on  $s$ , it invokes  $f(s)(r)$ , where  $r$  is the solving value of the predicate  $\hat{q}(r, s)$ <sup>4</sup>. The result  $v = f(s)(r)$ , if it is not null, will be later checked if it solves the current goal of the agent.

Figure 4 shows an example of an action to put a random cross on an empty square in a GoMoku board, if there is an empty square left. Indeed, this is not a very intelligent move. But the thing to note here is the action's guard. It inspects the environment to see if the game board still has empty squares (lines 7-8). If so, a random one, say  $sq'$ , will be returned (line 9). When the action is executed, this  $sq'$  will be passed to the function in the **do\_**-part, bound to the  $sq$  parameter. In this example, this will in turn call `move`, which will then place a cross on this square  $sq'$ .

<sup>4</sup> This scheme of using  $r$  essentially simulates *unification* as a pgrules in 2APL. Unification plays an important role in 2APL. The action in (1) corresponds to pgrule  $\hat{q}(r) ? | f(r)$ . The parameter  $s$  (the agent's state/belief) is kept implicit in pgrules. In 2APL this action is executed through Prolog, where  $\hat{q}$  is a Prolog query and  $r$  is obtained through unification with the fact base representing the agent's state.

### 3.2 Agent's deliberation cycle

Algorithm 1 shows how an aplib agent executes. It runs in typical BDI's sense-reason-act cycles, also known as *deliberation cycles* (Meyer, 2008; Dastani and Testerink, 2016; Rao and Georgeff, 1992). As we will see, aplib allows goals and tactics to be hierarchically structured. This provides a simple but powerful means for programmers to strategically program their agents, but on the other hand an agent now has additional tasks, namely to keep track of its current and next goal and tactic within the aforementioned hierarchies, as well as to regulate budget allocation. Consequently, Algorithm 1 is more elaborate than the base BDI algorithm as in (Rao and Georgeff, 1992).

Imagine an agent  $A = (s_{\rightarrow E}, \Pi, \beta)$ . The execution of  $A$  proceeds discretely in *ticks*. It sleeps between ticks (line 24), though an incoming message will awaken it.

At the start,  $A$  inspects its goal structure  $\Pi$  to determine which goal  $g_{\rightarrow T}$  in  $\Pi$  it should pursue (line 2). In the example in Fig. 3  $\Pi$  consists of only a single goal, so this is the one that will be selected.  $A$  then calculates how much of its budget  $\beta$  should be allocated for solving  $g$  ( $\beta_g$ ).  $A$  will then pursue  $g$ . This means *repeatedly* applying  $T$  over multiple ticks until  $g$  is solved, or  $\beta_g$  is exhausted. In BDI terminology, this reflects the promotion of  $g$  from goal to intent.

A single cycle of  $A$ 's execution is a single iteration of the loop in line 4. These are essentially what the agent does every cycle:

1. *Sensing*. The agent starts a cycle by sensing the environment (line 6/refreshing). This updates  $E$ 's state, and hence also the agent's state  $s$ .
2. *Reasoning*. To make itself responsive to changes in the environment, an agent only executes one action per cycle. So, if the environment's state changes at the next cycle, a different action can be chosen to respond to the change. Lines 7-9 represent the agent's reasoning to decide which action is the best to choose.

Let  $g_{\rightarrow T}$  be the agent's current goal, and  $T$  is the tactic that is associated with it to solve it. In the simple case,  $T$  is just a single action like in (1), though generally it can be composed from multiple actions. The agent determines which actions in  $T$  are enabled on the current state  $s$  (line 7). An action  $\alpha$  is enabled on  $s$  if it is eligible for execution on that state. Roughly, this means that its guard yields a non-null value when evaluated on  $s$ ; we will refine this definition later. If this results in at least one action, the method choose will choose one. The default is to select randomly. If no action in  $T$  is enabled, the agent will sleep (line 24),

```

1 Let  $A = (s_{\rightarrow E}, \Pi, \beta)$  be an agent.
2  $g_{\rightarrow T} \leftarrow \text{obtainCurrentGoal}(\Pi)$ 
3  $\beta_g \leftarrow \text{allocate budget for } g \text{ from } \beta$ 
4 while  $g \neq \text{null}$  do
5   if  $\beta_g > 0$  then
6      $E.\text{refresh}()$  // sensing the environment
7      $\text{actions} \leftarrow \text{obtainEnabledActions}(T, s)$ 
8     if  $\text{actions} \neq \emptyset$  then
9        $\alpha \leftarrow \text{choose}(\text{actions})$ 
10       $v \leftarrow \alpha.\text{execute}()$ 
11      for each  $G \in g.\text{ancestors}()$  do
12        |  $\beta_G \leftarrow \beta_G - \alpha.\text{s comp. cost}$ 
13      end
14      if  $v \neq \text{null} \wedge g.\text{evaluate}(v) = \text{true}$ 
15        then
16          mark  $g$  as solved.
17           $g_{\rightarrow T} \leftarrow \text{obtainCurrentGoal}(\Pi)$ 
18           $\beta_g \leftarrow \text{allocate budget for } g$ 
19          from  $\beta_{\Pi}$ 
20        end
21      else
22        |  $T' \leftarrow \text{next}(\alpha); T \leftarrow T'$ 
23      end
24    end
25    if  $g \neq \text{null}$  then
26      sleep until a tick or a message
27      arrives.
28    end
29  end
30  else
31    mark  $g$  as failed.
32     $g_{\rightarrow T} \leftarrow \text{obtainCurrentGoal}(\Pi)$ 
33     $\beta_g \leftarrow \text{allocate budget for } g \text{ from } \beta$ 
34  end
35 end

```

**Algorithm 1:** *The execution algorithm of an aplib agent. Lines 7 and 20 (blue) will be elaborated in Section 4, and line 12 in Section 6.*

hoping that at the next cycle the environment state changes, hence enabling some actions.

3. *Execution and resolution*. Let  $\alpha$  be the selected action. It is then executed. If its result  $v$  is non-null, it is considered as a candidate solution to be checked against the current goal  $g$  (line 14). If the goal is solved, the agent inspects the remaining goals in  $\Pi$  to decide the next one to handle, and the whole process is repeated again with the new goal. If there is no goal left, then the agent is done. If  $v$  does not solve the goal, at the next cycle the agent will again select which action to execute (Line 7). It may choose a different action. Things are now different than in non-tactical BDI

```

1 var T = FIRSTof(
2   action("win1") .do_(..).on_(winInOneMove).lift()
3   , action("defend") .do_(..).on_(danger).lift()
4   , ANYof( $\alpha_1$ ,  $\alpha_2$ )
5 )

```

Figure 5: Defining a tactic  $T$  for the GoMoku agent in Fig. 3, composed of three other tactics. The combinator `FIRSTof` will choose the first sub-tactic that is enabled for execution. The tactic "win1" is an action (the code is not shown) that would do a winning move, if win is achievable in one move. The tactic "defend" is also action; it will block the opponent if the latter can eminently move into a winning configuration. If winning in one move is not possible, and the agent is not in eminent danger of losing, the 3rd sub-tactic randomly chooses between two actions  $\alpha_1$  and  $\alpha_2$ .

agents. 2APL or GOAL agents use a flat structured plan-base, hence they always choose from the whole set of available plans/actions. In aplib, the structure of a tactic statically limits the choice of eligible actions (while actions' guards dynamically refine the choice). Deciding the next action to choose is therefore done in two stages: Line 20 inspect the tactic tree to first select which enclosing subtactic  $T'$  is eligible for the next cycle. The agent then sleeps until the next tick (or until a message arrives). Then, when the next cycle starts, Line 7 gathers all guard-enabled candidate actions within this  $T'$ , and then we do the rest of the cycle in the same way as before.

## 4 Tactic

Rather than using a single action, Aplib provides a more powerful means to solve a goal, namely tactic. A tactic is a hierarchical composition of actions. Methods used to compose them are also called *combinators*. Figure 5 shows an example of composing a tactic, using `FIRSTof` and `ANYof` as combinators. Structurally, a tactic is a tree with actions as leaves and tactic-combinators as nodes. The actions are the ones that do the actual work. Furthermore, recall that the actions also have their own guards, controlling their enabledness. The combinators are used to exert a higher level control over the actions, e.g. sequencing them, or choosing between them. This higher level control supersedes guard-level control<sup>5</sup>.

The following tactic combinators are provided; let  $T_1, \dots, T_n$  be tactics:

1. If  $\alpha$  is an action,  $T = \alpha.\text{lift}()$  is a tactic. Executing

<sup>5</sup>While it is true that we can encode all control in action guards, this would not be an abstract way of programming tactical control and would ultimately result in error prone code.

this tactic on an agent state  $s$  means executing  $\alpha$  on  $s$ . This is of course only possible if  $\alpha$  is enabled on  $s$  (if its guard results a non-null value when queried on  $s$ ). The execution of an action always takes a single tick.

2.  $T = \text{SEQ}(T_1, \dots, T_n)$  is a tactic. When invoked,  $T$  will execute the whole sequence  $T_1, \dots, T_n$ . This will take at least  $n$  ticks time (exactly  $n$  ticks if all  $T_i$ 's have no deeper `SEQ` construct).
3.  $T = \text{ANYof}(T_1, \dots, T_n)$  is a tactic that randomly chooses one of executable/enabled  $T_i$ 's and executes it. The 'enabledness' of tactics will be defined later.
4.  $T = \text{FIRSTof}(T_1, \dots, T_n)$  is a tactic. It is used to express priority over a set of tactics if more than one of them could be enabled. When invoked,  $T$  will invoke the first enabled  $T_i$  from the sequence  $T_1, \dots, T_n$ .

Consider a goal  $g \rightarrow T$ . So,  $T$  is the specified tactic to solve  $g$ . Recall that this means that the agent will repeatedly try  $T$ , over possibly multiple ticks, until  $g$  is solved or until  $g$ 's budget runs out. So, the execution of a tactic is implicitly always iterative. If  $T$  contains `SEQ` constructs, these will require the corresponding sub-tactics to be executed in sequence, hence introducing inner control flows that potentially spans over multiple ticks as well. This makes the execution flow of a tactic non-trivial. Let us therefore first introduce some support concepts.

If  $T$  is a tactic and  $s$  is the current agent state,  $\text{first}(T, s)$  is the set of actions in  $T$  that are eligible as the first action to execute to start  $T$ , and are furthermore enabled in  $s$ .  $T$  is said to be *enabled* on  $s$  if  $\text{first}(T, s) \neq \emptyset$ . Obviously, a tactic can only be invoked if it is enabled. Since enabledness is defined in terms of first, it is sufficient to define the later:

**Def. 1.**  $\text{first}(T, s)$  is defined recursively as follows:

- $\text{first}(\alpha.\text{lift}(), s) = \{\alpha\}$ , if  $\alpha$  is enabled on  $s$ , else it is  $\emptyset$ .
- $\text{first}(\text{SEQ}(T_1, \dots, T_n), s) = \text{first}(T_1, s)$ .
- $\text{first}(\text{ANYof}(T_1, \dots, T_n), s)$  is the union of  $\text{first}(U, s)$ , for all  $U \in \{T_1, \dots, T_n\}$ .
- $\text{first}(\text{FIRSTof}(T_1, \dots, T_n), s)$  is  $\text{first}(T_1, s)$ , if  $T_1$  is enabled on  $s$ , else it is equal to  $\text{first}(\text{FIRSTof}(T_2, \dots, T_n), s)$ , if  $n \geq 2$ , and else it is  $\emptyset$ .

Let  $\alpha$  be an action in a tactic  $T$ . After  $\alpha$  is completed, the agent will need to determine which action to do next. This is not only determined by the enabledness of the actions, but also the tactic sequencing imposed by `SEQ` and `FIRSTof` that are present in

$T$ . If  $U$  is a sub-tactic, let us define  $\text{next}(U)$  to be the next tactic that has to be executed after  $T$  is completed. Then it follows that the next action after  $\alpha$  is  $\text{first}(\text{next}(\alpha), s)$ , where  $s$  is the agent's current state. The definition is below:

**Def. 2.** Let  $U$  be a tactic. Since a tactic syntactically forms a tree, every sub-tactic, except the root, in this tree has a unique parent.  $\text{next}(U)$  is defined recursively as follows. Let  $U' = \text{parent}(U)$ .

- If  $U'$  is **SEQ**( $T_1, \dots, T_n$ ) and  $U = T_i$ ,  $i < n$ , then  $\text{next}(U) = T_{i+1}$ . If  $U = T_n$ , then  $\text{next}(U) = \text{next}(U')$ .
- If  $U'$  is **ANYof**( $T_1, \dots, T_n$ ) then  $\text{next}(U) = \text{next}(U')$ .
- If  $U'$  is **FIRSTof**( $T_1, \dots, T_n$ ) then  $\text{next}(U) = \text{next}(U')$ .
- If  $U$  has no parent (so it is the root tactic), then  $\text{next}(U) = U$ .

Now we can define how the tactic in  $g \mapsto T$  is executed. When the goal is first adopted the first actions eligible for execution are those from  $\text{first}(T, s)$  where  $s$  is the agent current state. In Algorithm 1 this is calculated in line 7. The function  $\text{obtainEnabledActions}(T, s)$  is thus just  $\text{first}(T, s)$ .

Suppose  $\alpha \in \text{first}(T, s)$  is selected. After this is executed, the agent first calculate which sub-tactic of  $T$  it should next execute. This is calculated by  $T' \leftarrow \text{next}(\alpha)$  in line 20 in Algorithm 1. When the new cycle starts, the next set of actions eligible for execution would be  $\text{first}(T', s)$ , which is again calculated by line 7. This goes on until the goal is solved. Notice that when all sequential sub-tactics of a top-level tactic  $T$  have been executed (which would take multiple ticks to do), the last case in the definition of  $\text{next}$  will return  $T$  itself as the next tactic to execute, essentially resetting the execution of  $T$  to start from its first action again.

## 5 Reasoning

Most of agent reasoning is carried out by actions' guards, since they are the ones that inspect the agent's state to decide which actions are executable. Fig. 4 showed an example of defining a simple action in `aplib`. Its guard (lines 6-9) queries the environment, representing a GoMoku board, to obtain an empty square, if there is any. The reader may notice that this query is imperatively formulated, which is to be expected since `aplib`'s host language, Java, is an imperative programming language. However, `aplib` also has a Prolog backend (using `tuprolog` (Denti et al., 2013)) to facilitate a declarative style of state query.

Figure 6 shows an example. To use Prolog-style query, the agent's state needs to extend the class

```

1 class AgentState extends StateWithProlog {
2   AgentState() {
3     addRules(
4       clause(winningMove("X", "Y"))
5         . IMPby(eastNeighbor(CROSS, "A", "B", "Y"))
6         . and(eastNeighbor(CROSS, "B", "C", "Y"))
7         . and(eastNeighbor(CROSS, "C", "D", "Y"))
8         . and(eastNeighbor(CROSS, "D", "E", "Y"))
9         . and(not(occupied("A", "Y")))
10        . and("X is A")
11        . toString(),
12        ... // the rest of winningMove's rules
13      ) }
14 }
15 var win1 = action("win1")
16 . do_((AgentState s) →
17   (Result r) → {
18     var x = intval(r.get("X"));
19     var y = intval(r.get("Y"));
20     s.env.move(CROSS, x, y);
21     return s.env.crossWin();
22   }
23 . on_((AgentState s) → s.query(st.winningMove("X", "Y")))

```

Figure 6: The definition of the "win1" action in Fig. 5. Its guard is formulated declaratively in the Prolog style.

`StateWithProlog`. It will then inherit an instance of a `tuprolog` engine to which we can add facts and inference rules, and then pose queries over these. The example shows the definition of the action "win1" that we had in Fig. 5, that is part of the tactic for the GoMoku agent in Fig. 3. The guard of this action searches for a move that would win the game for the agent in a single step. This is formulated by the query in line 22, which is interpreted as a Prolog-style query on the predicate `winningMove(X, Y)`. This in turn is defined as a Prolog-style rule/clause in lines 4-13. We do not show the full definition of the rule, but for example lines 5-10 characterize four crosses in a row, and an empty square just left of the first cross, and hence this empty square would be a solution for the predicate `winningMove(X, Y)` (putting a cross on this empty square would win the game for the agent). Notice that the rule is declarative, as it only characterizes the properties that a winning move/square needs to have; it does not spell out how we should iterate over the game board in order to check it.

## 6 Structured Goal

A goal can be very hard for an agent to solve directly. It is then useful to provide additional direction for the agent e.g. in the form of subgoals. For example, the GoMoku agent tactic in Fig. 5 is rather short sighted. Its only winning strategy, `win1`, is to detect a formation where the agent would win in the next move and then to do this move. An experienced opponent would prevent that the agent can create such

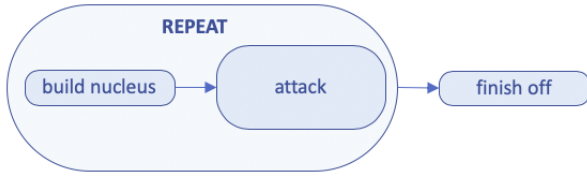


Figure 7: A human strategy to win GoMoku. The player first tries to create a nucleus of enough number of his pieces. Then, he switches to attack to create a configuration where win is inevitable in at most two steps. If he manages to do this then it is a matter of finishing off the game. Else, if after sometime the attacking strategy cannot reach its goal, the player reset the strategy by trying to create a new nucleus.

a formation in the first place. An example of a more sophisticated strategy is depicted in Figure 7, involving repeating two stages until a formation is created where win is inevitable no matter what the opponent does. Tactics are not the right instrument to express such strategies. A tactic is intended to solve a single goal, whereas the strategy in Figure 7 consists of multiple stages, each with its own goal.

In aplib we can express such a strategy as a complex/composite goal called a *goal structure*. It is a tree with goals as the leaves, and goal-combinators as nodes. The goals at the leaves are ordinary goals, and hence they all have tactics associated to each. The combinators do not have their own tactics. Instead, they are used to provide a high level control on the order or importance of the underlying goals.

Available goal-combinators are as follows; let  $G_1, \dots, G_n$  be goal structures:

- If  $g_{\rightarrow T}$  is a goal with a tactic  $T$  associated to it,  $g.lift()$  will turn it to a goal structure consisting of the goal as its only element.
- $SEQ(G_1, \dots, G_n)$  is a goal structure that is solved by solving all the subgoals  $G_1, \dots, G_n$ , and in that order. This is useful when  $G_n$  is hard to solve; so  $G_1, \dots, G_{n-1}$  act as helpful intermediate goals to guide the agent.
- $H = FIRSTof(G_1, \dots, G_n)$  is a goal structure. When given  $H$  to solve, the agent will first try to solve  $G_1$ . If this fails, it tries  $G_2$ , and so on until there is one goal  $G_i$  that is solved. If none is solved,  $H$  is considered as failed.
- If  $G$  is a goal structure, so is  $H = REPEAT G$ . When given  $H$  to solve, the agent will pursue  $G$ . If after sometime  $G$  fails, e.g. because it runs out of budget, it will be tried again. Fresh budget will be allocated for  $G$ , taken from what remains of the agent's total budget. This is iterated until  $G$  is solved, or until  $H$ 's budget runs out.

We can now express the strategy in Fig. 7 with a goal structure of the form:

```

var gomGoal =
  SEQ(
    REPEAT(SEQ( G1 // create a nucleus,
                G2 // attack)),
    G3) // finish off opponent
  
```

## Dynamic Subgoals

While there are plenty of problems that can be solved by decomposing it to a goal structure that remains unchanged through out the execution of the agent, for greater strength and more flexibility aplib agents can also dynamically insert new sub-goal-structures into its goal structure.

Let  $A$  be an agent and  $H$  a goal structure. The method  $A.addAfter(H)$  will insert  $H$  as a next sibling of  $A$ 's current goal. For example, if  $\Pi = SEQ(g_0, g_1)$  is  $A$ 's goal structure and  $g_0$  is the current goal,  $A.addAfter(H)$  will change  $\Pi$  to  $SEQ(g_0, H, g_1)$ . This is useful when the agent, upon inspecting the current state of the environment, concludes that in order to later solve the next goal  $g_1$  it is better to first solve  $H$ , so it introduces  $H$  as a new intermediate goal structure.

In a different situation  $g_0$  fails and the agent  $A$  notices that this is because some necessary condition is not met. What it can do is to restart the attempt to solve  $g_0$ , but this time inserting a new goal structure  $H$  aimed at establishing the missing condition.  $A$  can do so by invoking  $A.addBefore(H)$ . Note that, simply changing  $\Pi$  to  $SEQ(H, g_0, g_1)$  will not work, because the behavior of SEQ dictates that the whole SEQ fails if one of its sub-goal-structure fails. So instead,  $addBefore(H)$  changes  $\Pi$  to  $SEQ(REPEAT(SEQ(H, g_0)), g_1)$ . The REPEAT construct will cause the agent to move back to  $H$  upon failing  $g_0$ . The sequence  $SEQ(H, g_0)$  will then be repeatedly attempted until it succeeds. The number of attempts can be controlled by assigning budget to the REPEAT construct (budgeting will be discussed below).

## Budgeting

Since a goal structure can introduce multiple goals, they will be competing for the agent's attention. By default, aplib agents use the blind commitment policy (Meyer et al., 2015) where an agent will commit to its current goal until it is solved. However, it is possible to exert finer control on the agent's commitment through a simple but powerful budgeting mechanism.

Let  $\Pi$  be the root goal structure that is given to an agent to solve. For each sub-structure  $G$  in  $\Pi$  we can



specify a maximum on the budget it will get. Let us denote this by  $G.bmax$ . If left unspecified, the agent conservatively assumes that  $G.bmax = \infty$ . By specifying  $bmax$  we control how much the agent should commit to a particular goal structure. This simple mechanism allows budget/commitment to be specified at the goal level (the leaves of  $\Pi$ ), if the programmer really wants to micro-manage the agent’s commitment, or higher in the hierarchy in  $\Pi$  if he prefers to strategically control it.

When the agent was created, we can give it a certain initial computing budget  $\beta_0$ . If this is unspecified, it is assumed to be  $\infty$ . Once it runs, the agent will only work on a single goal (a leaf in  $\Pi$ ) at a time. The goal  $g$  it works on is called the *current goal*. This also implies that every ancestor goal structure  $G$  of  $g$  is also current. For every goal structure  $G$ , let  $\beta_G$  denote the remaining budget for  $G$ . At the beginning,  $\beta_\Pi = \beta_0$ .

When a goal or goal structure  $G$  in  $\Pi$  that was not current becomes current, budget is allocated to it as follows. When  $G$  becomes current, its parent either becomes current as well, or it is already current (e.g. the root goal structure  $\Pi$  is always current). Ancestors  $H$  that do not become current because they are already current will keep their budget ( $\beta_H$  does not change). Then, budget for  $G$  is allocated by setting  $\beta_G$  to  $\min(G.bmax, \beta_{parent(G)})$ , after we recursively determine  $\beta_{parent(G)}$ . Note that this budgeting scheme is *safe* in the sense that the budget of a goal structure never exceeds that of its parent.

When working on a goal  $g$ , any work the agent does will consume some budget, say  $\delta$ . This will be deducted from  $\beta_g$ , and likewise from the budget of other goal structures which are current (line 12 in Algorithm 1). If  $\beta_g$  becomes 0 or negative, the agent aborts  $g$  (it is considered as failed). It will then have to find another goal from  $\Pi$ . Since the budget of a goal structure is at most equal to that of its parent, the lowest level goal structure (so, a goal such as  $g$  above) is always the first that exhausts its budget. This justifies line 5 in Algorithm 1 that only checks the budget of the current goal.

Depending on the used budgeting unit it may or may not be possible to guarantee that  $\beta_G$  will never be negative. If this can be guaranteed, the above budgeting scheme also guarantees that the total used budget will never exceed  $\min(\Pi.bmax, \beta_0)$ .

## 7 Related Work

To program agents, without having to do everything from scratch, we can either use an agent ‘framework’, which essentially provides a library, or we use a dedicated agent programming language. Examples of agent frameworks are JADE (Bellifemine et al.,

1999) for Java, HLogo (Bezirgiannis et al., 2016) for Haskell, and PROFETA (Fichera et al., 2017) for Python. Examples of dedicated agent languages are JASON (Bordini et al., 2007), 2APL (Dastani, 2008), GOAL (Hindriks, 2018), JADEL (Iotti, 2018), and SARL (Rodriguez et al., 2014). HLogo is an agent framework that is more specialized for developing an agent-based simulation, which means that HLogo agents always operate on a fixed albeit configurable environment, namely the simulation world. On the other hand, JADE is a generic agent framework that can be connected to any environment. Aplib is also a generic agent framework, however it has been designed to offer the fluency of an embedded Domain Specific Language (DSL). It makes heavy use of design patterns such as Fluent Interface (Fowler and Evans, 2005) and Strategy Pattern (Gamma et al., 1994) to improve its fluency. Aplib is light weight compared to JADE. E.g. the latter supports distributed agents and FIPA compliance<sup>6</sup> which aplib do not have. JADE does not natively offers BDI agency, though BDI agency, e.g. as offered by 2APL and JADEL, can be implemented on top of JADE. In contrast, aplib, and PROFETA too, are natively BDI agent frameworks.

Among the dedicated agent programming languages, JASON, 2APL, and GOAL are dedicated for programming BDI agents. In addition to offering BDI concepts such as beliefs and goals, these languages also offer Prolog-style declarative programming. They are however rather restricted in available data types (e.g. no support for collection and polymorphism). This is a serious hinderance if we are to use them for large projects. JADEL and SARL are non-BDI. In particular SARL has a very rich set of language features (collection, polymorphism, OO, lambda expression). PROFETA, and aplib too, are somewhere in between. Both are BDI DSLs, but they are embedded DSLs rather than a native language as SARL. Their host languages are full of features (Python and Java, respectively), that would give the strength of SARL that agent languages like JASON and GOAL cannot offer.

Aplib’s distinguishing feature compared to other implementations of BDI agency (e.g. JACK, JASON, 2APL, GOAL, JADEL, PROFETA) is its tactical programming of plans (through tactics) and goals (through goal structures). An agent is essentially set of actions. The BDI architecture does not traditionally impose a rigid control structure on these actions,

<sup>6</sup> FIPA (<http://www.fipa.org/>) defines a set of standards for interoperation of heterogeneous agents. While the standards are still available, FIPA itself is no longer active as an organization.

hence allowing agents to react adaptively to changing environment. However, there are also goals that require certain actions to be carried out in a certain order over multiple deliberation cycles. Or, when given a hard goal to solve, the agent might need to try different strategies, each would need to be given enough commitment by the agent, and conversely it should be possible to abort it so that another strategy can be tried. All these imply that tactics and strategies require some form of control structures, although not as rigid as in e.g. procedures. All the aforementioned BDI implementations do not provide control structures beyond intra-action control structures. This shortcoming was already observed by (Evertsz et al., 2015), stating domains like autonomous vehicles need agents with tactical ability. They went even further, stating that Agent Oriented Software Engineering (AOSE) methodologies in general do not provide a sufficiently rich representation of goal control structures. While inter-actions and inter-goals control structures can be encoded through pushing and popping of beliefs or goals into the agent’s state, such an approach would clutter the programs and error prone. An existing solution for tactical programming for agents is to use the Tactics Development extension (Evertsz et al., 2015) of the Prometheus agent development methodology (Padgham and Winikoff, 2005). This extension allows tactics to be graphically modelled, and template implementations in JACK can be generated from the models. In contrast, Aplib provides the features directly at the programming level. It provides the additional control structures suitable for tactical programming over the usual rule-based style programming of BDI agents.

We also want to mention FATiMA (Dias et al., 2014), which is a BDI agent framework, but it extends agents’ BDI state with emotional states. At the first glance, emotion and tactical thinking would be considered as complementary, in situations where an agent has to work together with a human operator it would be reasonable to envisage the agent to take the human’s emotional state into account in its (the agent’s) tactical decision making. This can be done e.g. by deploying a FATiMA agent whose task is to model the user’s emotional state. While interesting, such a combination requires further research, and hence it is future work for us.

## 8 Conclusion & Future Work

We have presented aplib, a BDI agent programming framework featuring multi agency and novel tactical programming and strategic goal-level programming. We choose to offer aplib as a Domain Specific Language (DSL) embedded in Java, hence

making the framework very expressive. Despite the decreased fluency, we believe this embedded DSL approach to be better suited for large scale programming of agents, while avoiding the high expense and long term risk of maintaining a dedicated agent programming language.

While in many cases reasoning type of intelligence would work well, there are also cases where this is not sufficient. Recently we have seen rapid advances in learning type of AI. As future work we seek to extend aplib to let programmers hook learning algorithms to their agents. This will allow them to teach the agents to make the right choices, at least in some situations, which also means that they can then program the agents more abstractly.

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