

Explainable Composition of Aggregated Assistants

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Abstract

A new design of an AI assistant that has become increasingly popular is that of an “aggregated assistant” – realized as an orchestrated composition of several individual skills or agents that can each perform atomic tasks. In this paper, we will talk about the role of planning in the automated composition of such assistants and explore how concepts in automated planning can help to establish transparency of the inner workings of the assistant to the end-user.

Conversational assistants such as Siri, Google Assistant, and Alexa have found increased user adoption over the last decade and are adept at performing tasks like setting a reminder or an alarm, putting in an order online, control a smart device, and so on. However, the capability of such assistants remain quite limited to episodic tasks that mostly involve a single step and do not require maintaining and propagating state information across multiple steps.

A key hurdle in the design of more sophisticated assistants is the complexity of the programming paradigm – at the end of the day, end-users and developers who are not necessarily subject matter experts have to be able to build and maintain these assistants. A particular architecture that has emerged recently to address this issue is that of an “aggregated assistant” where the assistant is build out of individual components called skills. Skills are the unit of automation and they perform atomic tasks that can be composed together to build the assistant capable of performing more complex tasks. Prominent examples of this include IBM Watson Assistant Skills¹ and Amazon Alexa Skills².

This setup is not particularly confined to personal assistants either. An increasingly popular use of assistants is in enterprise applications. Here also, examples of aggregated assistant can be seen in offerings from Blue Prism³, Automation Anywhere⁴, and others. These individual skills belong to the class of Robotic Process Automation (RPA) tools that automate simple repetitive tasks in a business process.

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¹IBM Watson Assistant Skills <https://ibm.co/33f58Hc>

²Amazon Alexa Skills: <https://amzn.to/35xK2Xv>

³Blue Prism Digital Exchange: <https://bit.ly/2Ztzdla>

⁴Automation Anywhere Bot Store: <https://bit.ly/33hcr12>

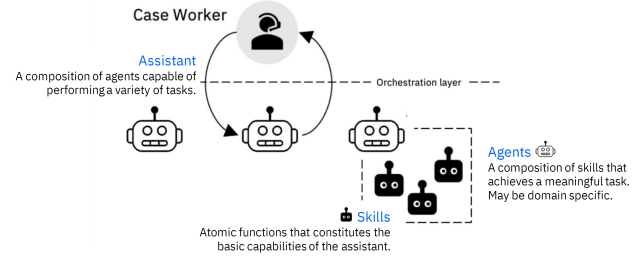


Figure 1: Simplified architecture diagram of Verdi (Rizk et al. 2020) illustrating the assistant-agent-skill hierarchy.

With recent advances in AI and conversational assistants, the scope of RPAs has also been evolving to take on more complex tasks, as we outline in (Chakraborti et al. 2020b). From the point of view of the planning community, this poses an interesting challenge: one of composing skills in a goal-oriented fashion to automatically realize assistants that can achieve longer-term goal-directed behavior. In (Chakraborti et al. 2020a) we demonstrated one such possibility of optimizing an existing workflow or business processes by composing it with skills to maximize automation and minimize case worker load. We showed how this design can be done offline by adopting a non-deterministic planning substrate. This design choice does not, however, readily lend itself to the automated composition of aggregate assistant – the composed assistant is going to evolve rapidly based on user interactions and it does not seem reasonable to model all possibilities over all goals up front.

Instead, in this paper, we will describe how we can use a rapid planning and re-planning loop to compose assistants on the fly. The first part of the paper will be outlining the implementation of this aggregated assistant in the form of a continuously evolving planning problem. One interesting outcome of this design is that a lot of the backend processes that affect the user interaction do not get manifested externally. In the second part of the paper, we will explore how concepts of causal chains and landmarks in automated planning will help us navigate transparency issues in aggregate assistants composed on the fly.

1 Aggregated Assistants

The particular aggregated assistant we will focus on is Verdi, as introduced in (Rizk et al. 2020) – architecturally, this subsumes all the examples above. Figure 1 provides a simple view of the system. An assistant in Verdi interfaces with the end-user (for a personal assistant) or case worker (for a business process assistant) in the form of an orchestrated set of agents, which are in turn composed of a set of skills.

Events The assistant is set up to handle and respond to different kinds of phenomenon in its environment – e.g. a text from the end-user, an alert from a service it is monitoring, a data object or a pointer to a business process, and so on. In general, we will call them “events” \mathcal{E} . In the examples in this paper, unless otherwise mentioned, we will deal with events involving user utterances only.

Facts The assistant also has access to a shared memory or knowledge base which stores global information known to the assistant – this is referred to as the Long Term Memory or LTM in Verdi. This information can be accessed by different agents and skills inside the assistant. We will refer to a variable in the LTM as a fact F with value f . For the purposes of this paper, this abstraction will be enough and we will not go into the details of the architectural implementation of the LTM. We will also assume that all variables in the LTM share the same vocabulary (more on this later).

Skills A skill, as we mentioned before, is an atomic function that performs a specific task or transform on data. Each skill ϕ is defined in terms of the tuple:

$$\text{Skill } \phi = \langle [[i, \{o\}_i], \dots], \delta \rangle$$

where $i \subseteq F$ and $o \subseteq F$ are the inputs and outputs of the skills respectively, and δ is the number of times the skill can be called in the lifespan of one user session. Notice that the outcome is a set: each member o_i is a possible outcome corresponding to the input i , and there are multiple such pairs of inputs and corresponding output sets for each skill.

For example, a skill that submits a credit card application for the user would need as an input the necessary user information and as output will either produce a successful or failed application status or may require further checks. It can also be pinged with a different input such as an application number to retrieve the status of the application.

Agents An agent can then be defined as the tuple:

$$\text{Agent } \Phi = \langle \mathcal{L}, \{\phi\}_i \rangle$$

where ϕ_i is its constituent skills and \mathcal{L} is the logic (e.g. a piece of code) that binds the skills together.

Every agent defines two functions:

$$\Phi.\text{preview} : \Phi \times \mathcal{E} \mapsto \mathbb{E}[\mathcal{E}]$$

This is the preview function ($\Phi.p$ in short) that provides an estimate of what will happen if an agent is pinged with an event. The output of the preview is an expectation on the actual output. In this paper this expectation will take the form of a probability that the

Algorithm 1: Verdi Flow of Control

```

while  $\mathcal{E}$  do
   $\{\Phi\}_i \times \mathcal{E} \mapsto \Phi_{eval}, \Phi_{eval} \subseteq \{\Phi\}_i$ 
  /* subset of agents to preview */
  foreach  $\Phi \in \Phi_{eval}$  do
    if  $\exists \Phi.\text{preview}$  then
       $\mathbb{E}_\Phi[\mathcal{E}] \leftarrow \Phi.\text{preview}(\mathcal{E})$ 
      /* compute expected outcomes */
    else
       $\mathbb{E}_\Phi[\mathcal{E}] \leftarrow \emptyset$ 
    end
  end
   $\{\Phi\}_i \times \{\mathbb{E}_\Phi[\mathcal{E}]\}_i \times \mathcal{E} \mapsto \Phi_{exe}, \Phi_{exe} \subseteq \{\Phi\}_i$ 
  /* subset of agents to execute */
  foreach  $\Phi \in \Phi_{exe}$  do
    return  $\Phi.\text{execute}(\mathcal{E})$ 
  end
end

```

agent can do something useful with the input event, thus: $\Phi.\text{preview} : \Phi \times \mathcal{E} \mapsto [0, 1]$.

Note that an agent may or may not have a preview. For example, if the evaluation requires a state change then an agent may not provide a preview: e.g. calling a credit score service multiple times can be harmful.

$$\Phi.\text{execute} : \Phi \times \mathcal{E} \mapsto \mathcal{E}$$

This is the execute function ($\Phi.e$ in short) that actually calls an agent to consume an event. Every agent must have an execute function.

Assistant The assistant can then be thought of as a mapping from an event and a set of agents to a new event:

$$\text{Assistant } \mathbb{A} : \mathcal{E} \times \{\Phi_i\} \mapsto \mathcal{E}$$

The exact nature of this mapping determines the behavior of the assistant – this is the orchestration problem.

2 Orchestration of an Aggregated Assistant

In this section, we will introduce how different orchestration patterns can be developed to model different types of assistants and describe the role of planning in it. Algorithm 1 provides an overview of the flow of control in an aggregated assistant, between the orchestrator and its agents.

Apriori and Posterior Patterns Following the flow of control laid out in Algorithm 1 there are two general strategies for orchestration:

- **apriori** where the orchestrator acts as a filter and decides which agents to invoke a preview on, based on \mathcal{E} ; and
- **posterior** where all the agents receive a broadcast and respond with their previews, and let the orchestrator pick the best response to execute.

These two strategies are not mutually exclusive. The apriori option is likely to have a smaller system footprint, but

involves a single bottleneck based on the accuracy of the selector which determines which agents to preview. The posterior option – despite increased latency and computational load – keeps the agent design less dependent on the orchestration layer as long as the confidences are calibrated.⁵

2.1 The S3 Orchestrator

The S3-orchestrator (Rizk et al. 2020) is a stateless, posterior orchestration algorithm that consists of the following three stages: Scoring, Selecting and Sequencing. Hence, the first step is to broadcast the event to all agents and solicit a preview of their actions: *this preview must not cause any side-effects on the state of the world in case the agent is not selected*. Once the orchestrator obtains the agents’ responses, it scores these responses using an appropriate scoring function so that the agents can be compared fairly (this where the normalization, as mentioned above, can happen, for example). After computing the scores, a selector evaluates them and picks one or more agents based on its selection criteria. One example is simply picking the agents that have the maximum score if greater than a threshold (referred to as *Top-K* selector). Finally, if more than one agent is selected for execution, a sequencer determines the order in which agents must execute to properly handle the event. Algorithm 2 details the process. Since agents’ executions may be dependent on each other, the order is important. Currently this is handled through simple heuristics and rules coded directly into the Sequencer. We will discuss later how planning and XAIP has a role to play here as well.

2.2 Stateful Orchestration using Planning

The S3-orchestrator does not maintain state and does not make any attempt to reason about the sequence of agents or skills being composed. In the following, we will go into details of a planner-based orchestrator that can compose agents or skills on the fly to achieve user goals. In comparison to the S3, this means we no longer need a selector-sequencer pattern: the planner decides which agents or skills to select and how to sequence them. In order to be able to do this effectively, we need to have the following external components.

Specification. The ability to compose agents on the fly requires a specification of agents in terms of (at least) their inputs and outputs.⁶ This is somewhat similar to applications of planning (Sohrabi 2010; Carman, Serafini, and Traverso 2003) in the web service composition domain (Srivastava and Koehler 2003). A necessary prerequisite to be able to use these variables from the shared memory across different agents and skills (developed independently and from

⁵This can be achieved by learning from agent previews over time and gradually adapting a normalizer or a more sophisticated selection strategy over the confidences self-reported by the agents, e.g. using contextual bandits (Sohrabi 2010). The ability to learn such patterns can also be used to eventually realize a healthy mix of apriori and posterior orchestration strategies.

⁶Of course, this can be extended to include additional rules relevant at the orchestration layer, such as ordering constraints (Allen 1983) to model preferred sequences: e.g. “*make sure do start with the chit-chat agent before anything else*”.

Algorithm 2: S3-Orchestrator

```

while  $\mathcal{E}$  do
  foreach  $\Phi \in \{\Phi\}_i$  do
    if  $\exists \Phi.preview$  then
       $P(\Phi) \leftarrow \Phi.preview(\mathcal{E})$  // confidence
       $S(\Phi) \leftarrow \text{Scorer}(P(\Phi))$ 
    else
       $S(\Phi) \leftarrow 0$ 
    end
  end
   $\Phi_{exe} \leftarrow \text{Selector}(\{S(\Phi)\}_i), \Phi_{exe} \subseteq \{\Phi\}_i$ 
   $\langle \Phi \rangle \leftarrow \text{Sequencer}(\Phi_{exe})$ 
  foreach  $\Phi \in \langle \Phi \rangle$  do
    return  $\Phi.execute(\mathcal{E})$ 
  end
end

Function  $\text{Scorer}(P(\Phi))$ :
  return  $P(\Phi)$  // default
return

Function  $\text{Selector}(\{S(\Phi)\}_i)$ :
  return  $\Phi_{ext} = \{\Phi \mid S(\Phi) \geq \delta\}$ 
  such that:  $|\Phi_{ext}| \leq k$  and
   $\nexists \Phi \in \Phi_{ext}, \Phi' \notin \Phi_{ext}$  with  $S(\Phi) > S(\Phi')$ 
  /* select top-k above threshold  $\delta$  */
return

Function  $\text{Sequencer}(\{\Phi\}_i)$ :
  return  $\text{List}(\{\Phi\}_i)$  // default
return

```

Algorithm 3: Planner-Based Orchestration

```

while  $\mathcal{E}$  do
   $\mathcal{G} \leftarrow \text{Derive-Goal}(\mathcal{E})$ 
   $\langle \Phi \rangle \leftarrow \text{Planner}(\{\Phi\}_i, \mathcal{G}, \mathcal{E})$ 
  foreach  $\Phi \in \langle \Phi \rangle$  do
    return  $\Phi.execute(\mathcal{E})$ 
  end
end

```

different sources) is that they share some vocabulary. This needs to be enforced on the specification through the use of some schema or ontology to ensure consistency up front, or by fuzzy matching variable names on the fly during execution. Existing works in using planning for web service composition have explored advanced technique on this topic (Hoffmann, Bertoli, and Pistore 2007; Weber 2009; Hepp et al. 2005; Sirin et al. 2004). As we mentioned before, for this paper, we assumed that the skill and agent specifications share the same vocabulary.

Goal-reasoning engine. Finally, the composition at the orchestration layer requires a goal: the planner-based orchestrator produces goal-directed sequences of agents and skills. This goal is something that is derived from events and

is usually related to something the user is trying to achieve. However, this may not always be the case. We will go into further details of this in the next section.

3 Stateful Orchestration using Planning

We will now go into the details of implementation of the planner-based orchestrator, and then a detailed example of it in action. This will help us better understand the XAIP issues endgendered by automated orchestration of an aggregated assistant and the details of the proposed solution.

3.1 Agent and skill specification

The central requirement to start converting the agent sequencing problem into a planning problem is some form of a model of how the skills and agents operate. We want to keep the specification as simple as possible and move as much of the specifics of orchestration patterns to the execution component as possible (where we can leverage the evaluate option whenever possible). This not only lets us alleviate some of the modeling overhead from developers but also allows us to keep the planning layer light thus allowing us to perform rapid execution and replanning. A skill or agent specification (Figure 2) contains the following information:

1. The function endpoint of the skill or agent.
2. A user understandable description of what it does (to be used in generating explanatory messages).
3. An upper limit on the number of times the assistant can retry the same skill or agent to get a desired outcome.⁷
4. And finally, an (approximate) specification of functionality (as described in Section 1). as a set of pairs of tuples of input and possible output pairs that represents roughly the various operational modes of the skills.

For example, a visualization skill could take raw data and generate the plot that it believes best represents that data or it could take the data along with the plot type to create the specified plot. Each pair consists of a set of inputs the skill or agent can take and specifies a set of possible outputs that could be generated by the skills for those inputs. The possible output set consists of mutually exclusive sets of output that may be generated. These can be thought of as the non-deterministic effects of the skills, though in the next section we will discuss how these scenarios diverge from traditional non-deterministic planning settings. Special inbuilt skills (we will see some examples of these later in Section 3.5) in Verdi also get an entry in the specification with a similar structure to above, but we do not require them to refer to elements in the ontology. They may use keywords that may map to specific compilations when we build the planning model out of the specification.

⁷This is important since you may not want the assistant to, for example, ping a credit score retrieval skill more than once and inadvertently reduce the credit score of the user, or you may not want the assistant to get stuck at a disambiguation question to fill a slot when it cannot detect the utterance multiple times.

```
information_that_needs_authentication:
- account_number
- income
- credit_score

skill_spec:
  loan_skill:
    type: skill
    actuator: verdi_skill_samples.planner_demo...
    skill_information: "loan request process"
    specification:
      -
        number_of_retries_allowed: 1
        input:
          - account_number
          - income
          - credit_score
          - valid_id
          - loan_amount
        output:
          - loan_processed
```

Figure 2: A sample specification of a skill.

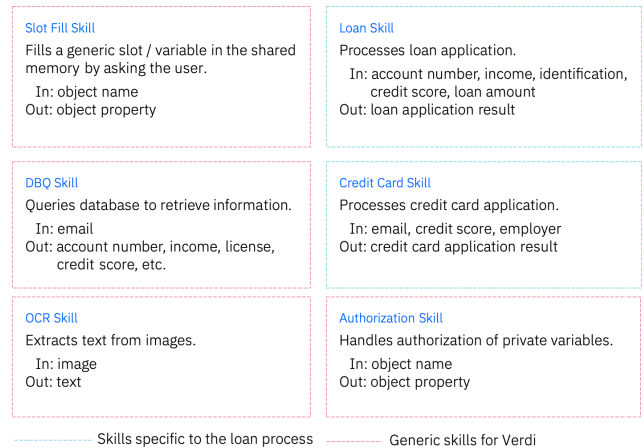


Figure 3: The catalog used in Figure 5.

3.2 Compilation to PDDL

The next step is to convert the agent specification into a planning model. Given our problem is closely related to non-deterministic planning, we decided to map the agent specification into a non-deterministic planning model with additional considerations provided to support problem elements that are uncharacteristic of standard non-deterministic planning problems. More on this later in Section 3.4.

In terms of modeling, we create a type for each element that appeared in the specification and we created a type for each individual input-output pairs of the skill function specification. We create a one objects for each element type and

one object each for the pairs. From the shared ontology, we also incorporate the subsumption information into the planning model by converting it into a type hierarchy (e.g. a pie chart is a type of plot – so if a skill can return a pie chart it can also try to respond to a request for a plot). In order to use popular off-the-shelf planners this means restricting the relations to a tree-like hierarchy.

We are interested in establishing the value of different variables in the shared memory so that the relevant skills and agents can be invoked with the requisite knowledge required for their operation (as per their specification). Thus, the central fluent of the planning problem is (known - ?x). The planner itself does not care about the specific value that each variable takes but rather reasons with the signature of each variable, i.e. whether their value is known or not, or whether it was attempted and cannot be known.

In terms of action specification, we made use of an all outcome determinization (Yoon, Fern, and Givan 2007) of the non-deterministic model to plan with. For each skill ϕ , whose functional specification can be represented by the tuple $\phi = \langle ([i, \{o\}_i], \dots) \rangle$, we create a different action for each possible input and output pair. So just for the tuple $(i, \{o_i^1, \dots, o_i^k\})$ we create k possible lifted actions each meant to capture the ability of the skill to achieve the specific outcome. For each action $a_{1,1}^\phi$, the precondition enforces that the value of each input element in i is known and the effects ensure that for each output element in o_i^1 the known value corresponding to that element is set to true.

Internal Skills and Other Constraints Unlike the external skills, we allow for more flexibility when compiling internal skills. For example, in the example considered later, we have two internal skills. A slot filling skill that allowed querying the user for the value of a specific element (which basically has an add effect that sets that element to be known) and an authorization skill that authorizes the use of certain skills over sensitive information. In addition to the specific compilation of inputs and outputs, we also allow the inclusion of more global constraints. One of the examples, we had was this need to perform authorize action before sending sensitive information (listed in the specification) to skills. We did this by adding an authorize precondition to skills that took sensitive information as an input.

3.3 Goal Reasoning Engine

The final component of the planner-based orchestrator is the goal: the sequences composed will be trying to achieve this goal. A goal can come from many sources:

- The most common goal is derived from the user utterance. Every time a user utterance is received, the goal reasoning engine analyzes it and ascribes a symbolic goal to it. The example in Section 3.5 is of this type. In most cases, is just to set the value of an element to known, but in general, it is a partial state that may be a conjunction that calls for the value of several such elements to be determined – e.g. a user goal to take a holiday can resolve to a requirement that a hotel and a flight is booked.
- We mentioned before than an user utterance is just one form of an event in the system. There could be other

events that trigger a goal – e.g. a user in a DevOps domain can ask the assistant for a web service to be brought up and this can be a maintenance goal. The planner will be triggered in this scenario when an alert pops up notifying that the service has gone down.

- Goals may be implicit as well – e.g. in Algorithm 2 the proposed orchestrator can take the Sequencer’s role. Then the implicit goal is just to make sure that the set of agents returned by the Selector are sequenced correctly.

Usually, the mapping from user utterance to goals is a domain-specific one and needs to be specified for each agent. The initial state is provided by the current set of known values for each element. This completes the compilation of the orchestration problem to a planning problem.

We maintain the current set of goals as a stack. Every request from the user gets pushed onto the stack as a new goal. At any given time the assistant focuses on achieving the goal on top of the stack and whenever the current goal is completed (or stopped as per the user’s request), the assistant falls back to the previous goal on the stack. Each time it moves to the previous goal, the user is notified about the new goal being pursued, giving them an opportunity to either stop or add a new goal. The goal stack can also be used to augment an interaction with new goals: e.g. the assistant can prompt the user for a new credit card when a loan application is completed. Such goal extensions need to be specified by the developer but can also be learned from statistical patterns over repeated interactions with end users.

3.4 Learning Through Execution

As mentioned earlier, the setting we are looking at is not the standard non-deterministic planning setting studied in literature. In fact, many of the non-deterministic aspects of skill execution could be tied to unobservable factors and incomplete specifications. In such cases, many of the standard assumptions made for non-deterministic planning like fairness (Sardina et al. 2015) is no longer met (Srivastava, Russell, and Pinto 2016; Illanes and McIlraith 2019). Thus we cannot directly apply traditional non-deterministic planning but we will use the information gathered through observation of execution to overcome such limitations. Currently, we allow for two such mechanisms:

Loops. To prevent the system from getting trapped in loops trying to establish specific values, we introduce a new predicate called `cannot_establish` that takes in two arguments: the skill (or more specifically the skill input-output pair) and the element in question. For each output of an action, we add a negation of `cannot_establish` for the corresponding output element and the skill pair corresponding to that skill into the precondition. This means that if the value for the predicate is set true in the initial state then the action would not be executed. This value is established by the central execution manager, that monitors all the skills that have been executed till now and maintains a counter of how many times a skill has been unsuccessfully called to establish some value. When the counter crosses the limit set in the specification, the corresponding value is set in the initial state for all future planner calls.

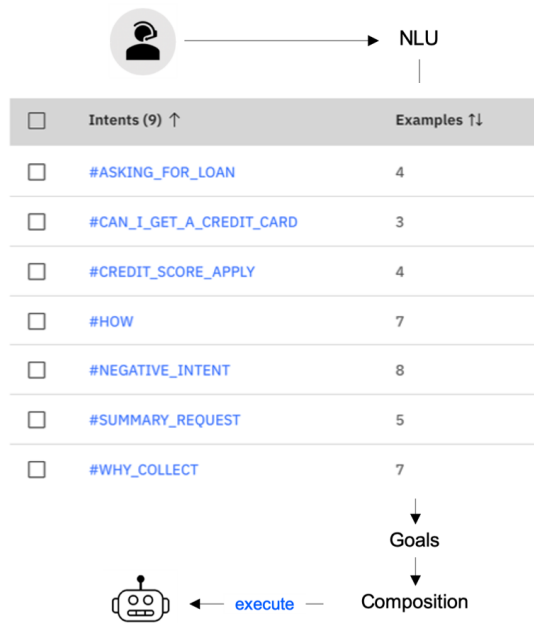


Figure 4: The entity recognizer inside the goal reasoning engine. Some intents (e.g. loan or credit card) correspond to user goals while others (how or why questions) are used to manage domain-independent conversation patterns.

Model Refinement. The next problem we wanted to address is that these specifications are inherently incomplete. Thus the planner may try to call the skills using values that may not be valid or expect outputs for certain inputs that the skill may not be able to generate: e.g. not all variables can be slot-filled through conversation with the user. We expect currently that such situations can be detected by either the skill itself or the execution manager and once such an incorrect invocation of the skill is detected the corresponding grounded action is pruned out of the model.

3.5 Illustrative Example

We use a sample banking scenario to illustrate key properties of the composed aggregated assistant. The assistant here is meant to help users in a banking domain with submitting a loan and credit card applications, which includes gathering relevant information from the users and submitting them to the appropriate channels and reporting the results.

The agent has access to a catalog of skills (Figure 3) including ones that submit the loan or credit card applications, a skill to perform OCR, a skill to retrieve information from a database (from where it can retrieve records by providing the user’s email id or account number). The agent also has access to two Verdi internal skills: the slot filling skill gathers information from the user for variables in the shared memory⁸ and an authorization skill meant to confirm with users whether to send sensitive information to the skills.

⁸The implementation of the slot filling skill determines which slots can be filled. This is not part of the specification and thus not known to the planner: it gets to know when it executes.

The goal reasoning engine includes an NLU component (Figure 4) capable of recognizing a number of intents, including asking for a loan, a credit card, requesting to retrieve and display information, asking for explanations, summaries, and to stop the current request, and so on. Each intent is translated to their symbolic goals and managed by the goal reasoning engine at the time of execution.

Figure 5 provides step by step details of the orchestration patterns and the plans created and discarded in the background. A few salient features below:

Goal Seeking Behavior Clearly noticeably is the goal seeking behavior of the orchestrator. At any moment it tries to create the shortest sequences of agents or skills for its catalog so as to achieve a goal. This is the primary reason to use a planner-based orchestrator and it motivates a new class of aggregate assistants that can move beyond the episodic or one-shot interactions afforded by the state of the art.

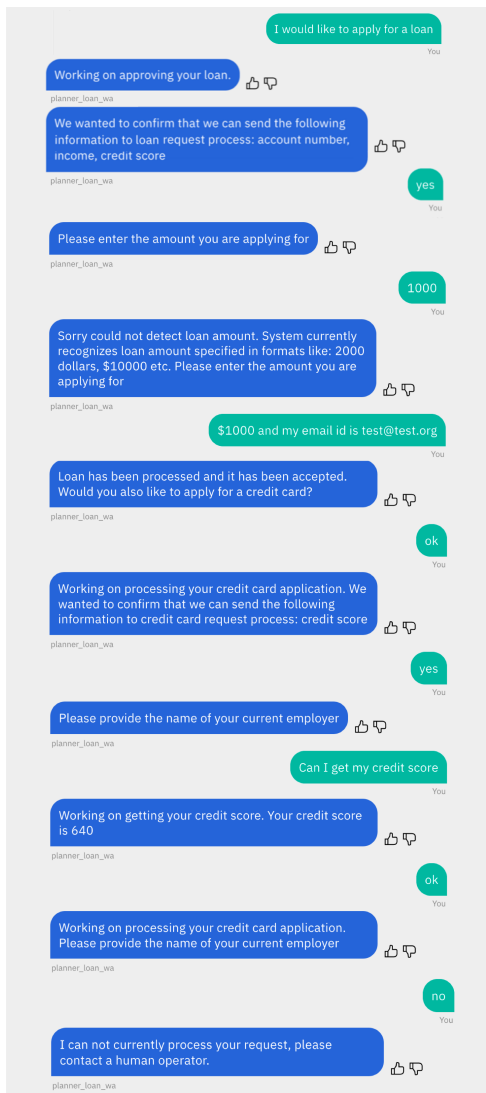
Graceful Digression One powerful feature of having an orchestrator than maintains state is to be able to digress gracefully. This involves: 1) Asking again if something is not clear; 2) Parsing additional or seemingly unrelated information for other goals; and 3) Switching to a new goal if necessary and switching back to the old one, once done. Modeling digression patterns well is essential to conversational assistants and we posit that using a stateful orchestrator is the only way to induce such behavior. Graceful digression patterns is a direct consequence of the goal stack.

Authentication and Privacy Finally, one particular concern in the composition of an aggregated assistant is that of the information that will eventually get distributed across the various agents, skills, and services plugged into it. We experimented with two privacy models: one where every skill or agent is authenticated once at the time of sharing and one where each data element is authenticated once at the time of fetching. The former requires less back and forth with the user and so we went with this as the default.

4 Automated Orchestration and XAIP

Even though using planners to compose stateful orchestration patterns on the fly allowed us to model the complex conversational patterns above, from the end-user perspective, we have a problem: in the example in Figure 5 we noted the internal processes going on in response to the user utterances but none of this is actually visible to the user. This means when the goal is achieved, a series of events have unfolded in the background for the assistant to reach that conclusion unbeknownst to the user. As such, this can be quite unsettling, as seen in the sudden response with the loan result after a couple of interactions with the assistant acquiring information from the user. We propose to navigate this situation of the automated orchestration approach using what”, “how”, and “why” questions. There are many reasons to surface the internal processes to the end-user on demand:

- The transparency of automated compositions for the user of the assistant who cannot see the plans being made and discarded in the background;



Goal Reasoning: Push a new goal.

Privacy: Manage permissions when sharing user data across skills.

1. Not a real digression → need to ask again.

2. Not a real digression i.e. not what we are looking for but information that can be used elsewhere → parse & continue/clarify.

Goal Augmentation: Push a new goal based on needs of the admin and/or statistical analysis of user patterns.

3. A “real” digression → switch to the new goal.

Graceful Digression = 1 + 2 + 3

Goal Persistence: Pop old goal after current process is complete.

If no plan is found that achieves user goal, fall back to human agent.

Planner attempt – 1

Step 0: slot_fill_skill (loan_processed)

Plan failed.

Planner attempt – 2

Step 0: auth_skill (loan_skill)

Step 1: slot_fill_skill (loan_amount)

Step 0: slot_fill_skill (loan_amount)

Step 1: slot_fill_skill (account_number)

Step 2: slot_fill_skill (credit_score)

Step 3: slot_fill_skill (income)

Step 4: slot_fill_skill (valid_id)

Step 5: loan_skill (account_number, income, credit_score, valid_id, loan_amount)

Unexpected state: re-plan.

Planner attempt – 3

Step 0: dbq_skill (email_id, account_number, income, credit_score, license_screenshot)

Step 1: ocr_skill (license_screenshot, valid_id, ocr_skill)

Step 2: loan_skill (account_number, income, credit_score, valid_id, loan_amount)

Success.

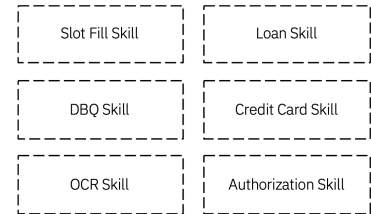


Figure 5: Detailed example illustrating stateful orchestration of skills in the assistant to achieve evolving user goals in the banking domain. A sample conversation with the assistant is embedded on the left, the middle provides highlights of interesting stateful orchestration patterns, and finally, the right illustrates the evolving plans in the backend to support this conversation.

- Above, where the end-user is a subject matter expert who can use the explanations to affect better compositions;
- Above, where the end user has a right to an explanation, as per GDPR guidelines (Kaminski 2019). Even though such guidelines may not apply to the constraints of the underlying process (Wachter, Mittelstadt, and Floridi 2017), they do certainly apply to data subjects of which the user is one, as is evident in the examples provided where multiple skills and agents fetch and use user information in the background to achieve user or system goals.

4.1 “What?” Questions

The first step towards achieving transparency is to be able to provide summaries (Amir and Amir 2018; Sreedharan, Srivastava, and Kambhampati 2020) of what was done in the

backend back to the user. Instead of simply dumping the entire steps of the plan, our focus here was to provide only the most-pertinent set of information to the user and provide them with ability to drill down as required. This is motivated not just by the fact that the plan may have many steps, but also by the online nature of the planning problem – the agent may have performed steps that were in the end not pertinent to the final solution. To provide information central to achieving the goal, we extract the landmarks corresponding to the goal from the original initial state, since regardless of the exact steps all information corresponding to landmark facts should have been collected to get to the goal.

Such techniques have been used recently to summarize policies (Sreedharan, Srivastava, and Kambhampati 2020). Unlike those cases, the system here is also learning about the domain during execution. So we also need to incorporate

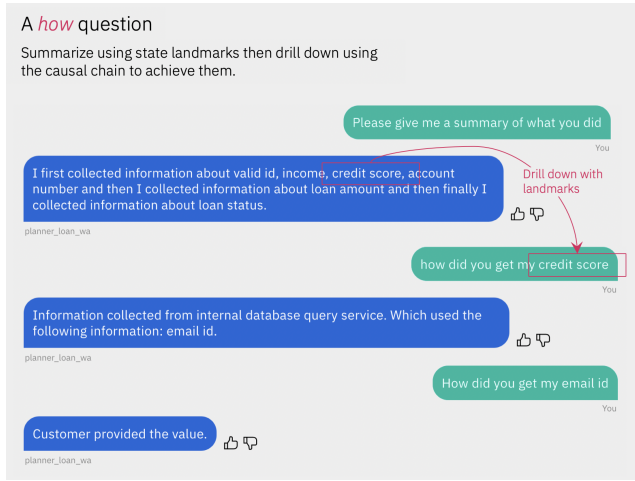


Figure 6: Example of a summary followed by the user drilling down with “how?” questions.

any `cannot_establish` facts that have been learned along the way into the initial state and also remove any actions that may have been pruned along the way. This means even though the first time the planner was called, it believed it could establish the goal with a single step, through the execution it realized it needs to gather multiple information items. Figure 6 shows the summary generated for the current demo domain.⁹ The actual summary text presented to the user uses a template-based generation, that relies on ordering between the landmarks generated via a topographical ordering of landmarks corresponding to the establishment of information (while ignoring all compilation specific fluents).

4.2 “How?” Questions

Once a summary is provided, we allow the user to drill down on any aspect of it by asking how that was achieved. This involves identifying the agent or skill that established the value of the element and providing that detail to the user. Here we rely on the simple description provided by the skill author in the specification. In addition to showing the skill, we also provide the inputs that the skill took, so that if the user requires they can chain even further back.

4.3 “Why?” Questions

Furthermore, the user can also go forward from that fact and explore why that was required to be established, in terms of its role in achieving the goal. We adapt the popular idea of using the causal chain from an action to the goal as the justification for its role in the plan (c.f. (Veloso 1992; Seegebarth et al. 2012; Bercher et al. 2014; Chakraborti et al. 2019; Kambhampati 1990)) to individual facts. We identify whether an action contributed something to the goal by performing a regression from the goal over each action that was executed by the agent. For a skill execution that took as

⁹This currently uses a topological sort of landmark ordering and then filters out the compilation specific variable. Moving forward, we plan to use the actual order in which data was collected.

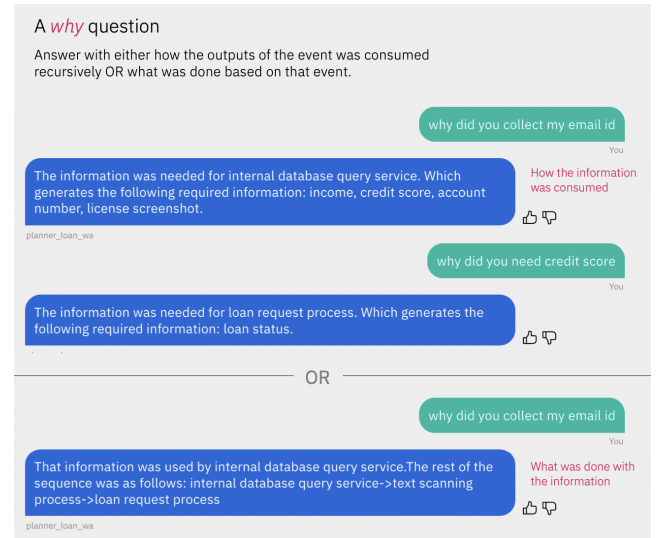


Figure 7: Example of two ways to answer “why?” questions.

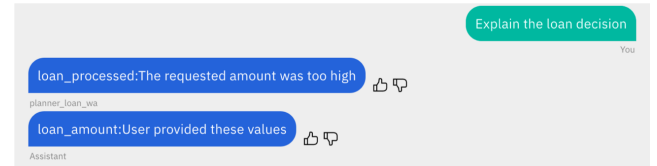


Figure 8: Example of augmenting the explanation of the orchestration process with that of a decision made by a skill.

input the set of facts i and generated an output set σ_i^j , for a current regressed state s_i , the next state s_{i-1} is provided as $(s_i \setminus \sigma_i^j) \cup i$. Now we can allow for the fact that the system may have made missteps, by ignoring any actions that do not contribute something to the current regressed state. We stop as soon as we reach an agent or skill that contributes to the regressed state and used the fact in question. We can either provide the full causal chain to the goal (by build such chains on the fly from the goal during the regression process) or just provide this final action.

4.4 Work in Progress: Explanation Chaining

The above discussions were focused on generating explanations for the orchestration patterns only but do not try to explain why the individual agents and skills made the decisions they made. They may be using AI components to generate their decisions and we may want the explanations for these individual decisions to be provided by the agent or skill itself. Thus, we envision a third component of an agent (c.f. Section 1): $\Phi.explain$ which provides an explanation of its output in terms of its inputs, much like feature attribution explanations (Sundararajan and Najmi 2020).

For example, the loan approval skill might say your credit score is too low. The system can provide assistance here is by tracing the source of such information: e.g. it can go back and identify where it found the credit score that was passed to loan approval skill. This creates a chain of skills, with

the explanation for the output of one agent skill being clarified with an explanation from another. Currently, the chain is terminated, when the backward chaining reaches an information that is known to the user (such as one specifically provided by them). For now, we limit chaining to the feature with the highest weight as attributed by the explanation.

5 Conclusion and Future Work

In this paper, we introduced a new type of (conversational) assistant that is becoming increasingly popular: an “aggregated assistant” realised as an orchestrated composition of skills and agents. We looked at the role of automated planning in it, in how it can facilitate the automated composition of such assistants, and this can lead to loss of transparency. We showed how techniques from the XAIP community in surfacing causal information of planning domain to end users can help in mitigating such concerns of transparency in automatically constructed aggregate assistants. In the following, we expand on the presented ideas with some interesting avenues of future work.

What is a goal? In the approach described in the paper, we only talked about “logical” goals derived from the user utterance. This does not always have to be a case. A more general form of a goal are “metric” goals – these are observed metrics of the processes being modeled by the assistant. In the planning parlance, these can often be modeled as numeric fluents (Fox and Long 2003) as properties of an individual skills or agents: e.g. their health, accuracy, money cost, etc. But not always. Cases where it is difficult to model metric goals is when they are properties of the entire process and not individual actions in the domain – this becomes harder when such properties are ill defined. Examples include customer satisfaction, timespan of processes (when they are not modeled), overall expertise requirement of a process, and so on. In the context of business processes, these are often referred to as Key Performance Metrics (Parmenter 2015) that the system admin monitors and cares about, and eventually we would want to compose assistants that cater to the desired “KPI goals” of the composed assistant: e.g. “achieve compositions with target metric \mathcal{M} ” based on historical data.

Another avenue of extension here is in the way the logical goals are extracted from the user utterance. Currently, as we outlined in Section 3.3, we use intent classifiers coded in by the developer of the assistant. This, again, requires modeling overhead. There are two possible ways to get around this. One can match the user utterance to the specification and natural language description of a skill or agent in the catalog and use (the use of) that component as the end goal. This requires less modeling overhead but is also less expressive since, in general, goals are attributed to a state of the system which may not correspond to the effects of a specific skill: e.g. a goal to book a trip would require hotel, flight, etc. The other way to slowly generate this mapping is to use a “cold starting” scheme, as described below.

Cold starting the orchestrator. One of the topics we discussed in Section 3.4 was the refinement of the skill and agent specifications over time by learning from execution

Algorithm 4: Explanation Flow of Control

```

 $\mathcal{G} \leftarrow$  Goal set
 $\mathcal{H} \leftarrow$  Execution History // A sequence of
    tuples  $\langle i, \phi, o_i \rangle$  ending at the goal
while  $\mathcal{E}$  do
     $\mathcal{G}, f \leftarrow$  Derive-Goal ( $\mathcal{E}$ )
    if  $\mathcal{G} \rightarrow$  “Why” then
        | Why-next-action ( $f$ )
    end
    else if  $\mathcal{G} \rightarrow$  “How” then
        | How-last-action ( $f$ )
    end
    else if  $\mathcal{G} \rightarrow$  “What” then
        | Landmark-Extractor ( $f$ )
    end
end

Function How-last-action ( $f$ ):
    for  $\langle i, \phi, o_i \rangle \in \mathcal{H}$  do
        if  $f \in o_i$  then
            | return  $(i, \phi)$ 
        end
    end

Function Why-next-action ( $f$ ):
     $\mathcal{R} \leftarrow \mathcal{G}$ 
    for  $\langle i, \phi, o_i \rangle \in \text{Reverse}(\mathcal{H})$  do
        if  $\mathcal{R} \subseteq o_i$  then
            |  $\mathcal{R} = (\mathcal{R} \setminus o_i) \cup i$ 
        end
        if  $f \in i$  then
            | return  $\phi$ 
        end
    end

Function Chain-explanation ( $f$ ):
    while  $f$  is not provided by user do
         $i, \phi \leftarrow$  How-last-action ( $f$ )
         $\phi.\text{explain}(f)$ 
    end

```

patterns. This can help out especially in reducing the modeling overhead on the developer or the admin of the assistant. One can start off with a minimal specification and an S3-orchestrator, observe a few interactions (or simulate the assistant) and refine those specifications over time, before activating the planner-based orchestrator. The latter buys us the more complex stateful orchestration patterns as we discussed; and this “cold start” scheme reduces the need for detailed or complete specifications up front. There are many existing approaches to learning PDDL models from traces (Gil 1994; Zhuo, Nguyen, and Kambhampati 2013); including ones that extend PDDL (Nguyen, Sreedharan, and Kambhampati 2017) to handle the incompleteness of the learnt model in terms of *possible* conditions.

Agent Preview. Finally, you may have noticed, that we never used the agent preview in the planning-based orches-

trator. That is because the planner chose a composition and only replanned at the time of execution: this flow meant that, as compared to the S3-orchestrator, the planning-based orchestrator had no separate selector and sequencer. That is just the job of the planning problem.

However, this flow also means that there will be frequent calls to replan when the execution fails; and this will affect the assistant's time to response to the end user. The way to mitigate this would be to use the preview in the planning process itself to compute higher fidelity plans. This is an optimization in the backend and not immediately visible to the end user (in terms of quality of compositions) unless it affects the latency. Interestingly, this can also help the orchestrator to deal with agents or skills that may change state and thus should not be executed blindly, and even to hand-off some of the specification overhead to the implementation of the agent or skill itself so that they can respond with possible outcomes of an execution call in the preview call.

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