Strategic Planning for Network Data Analysis

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Abstract

As network traffic monitoring software for cybersecurity, malware detection, and other critical applications becomes increasingly automated, the rate of alerts and supporting data gathered, as well as the complexity of the underlying model, regularly exceed human processing capabilities. Many of these applications require complex models and constituent rules in order to come up with decisions that influence the operation of entire systems. In this paper, we motivate the novel strategic planning problem – one of gathering data from the world and applying the underlying model of the domain in order to come up with decisions that will monitor the system in an automated manner. We describe our use of automated planning methods to this problem, including the technique that we used to solve it in a manner that would scale to the demands of a real-time, real-world scenario. We then present a PDDL model of one such application scenario related to network administration and monitoring, followed by a description of a novel integrated system that was built to accept generated plans and to continue the execution process. Finally, we present evaluations of two different automated planners and their different capabilities with our integrated system, both on a six-month window of network data, and using a simulator.

1 Introduction

As the reach of the internet grows, network traffic monitoring software for malware detection, cybersecurity, and other critical applications is becoming increasingly important and is being used in larger deployments than ever before. Often, this increase in use brings with it a manifold jump in the amount of data that is collected and subsequently generated by the application, and an increase in the importance of the processes that are used to analyze that data. Usually, these processes are codified as sets of rules that are applied to the incoming data. These rules are often only known to domain experts, whose job it is to sift through the data and arrive at decisions that will determine the future of the system as a whole. However, given that these experts are human, an explosion in the size of the incoming data as well as its complexity renders this manual approach grossly infeasible and worse, susceptible to errors and catastrophic failure. Such eventualities motivate the general task of automating the processes that the experts undertake in analyzing the data. We call this the strategic planning problem.

The aim of strategic planning is to consider all the components and data at the system’s disposal and come up with a sequence of decisions (actions) to achieve, preserve or maximize some specific objective. The strategic planning process may be closed loop, i.e., decisions are made based on the data currently available, but may change given new data that is sensed from the world, or otherwise provided. We look to apply automated planning methods, and planners, as mediators to this strategic planning problem. The advantage of framing this as a planning problem is that we can use multiple levels of planners, and different models, in order to represent the different facets of the system. This enables us to expose the system to various experts and their knowledge at different levels of detail. A single system that takes just one model of the domain into consideration would either fail to scale to the large amounts of data that the system must process, or make very little sense representationally to the experts whom the system is designed to assist.

A few previous approaches have considered employing automated planning methods and terminology to the processing of streaming data and the composition of system components, as a limited version of the strategic planning problem. The closest such work is that of Riabov and Liu (Riabov and Liu 2006), who developed a specialized version of a Planning Domain Definition Language (PDDL) based approach to tackle a real streaming problem. However, that approach focused on producing a single analysis flow for a given goal, and did not support investigations that involve multiple decisions based on sensing actions. Other methods have been proposed, consisting of more specialized approaches where composition patterns are specified (Ranganathan, Riabov, and Udrea 2009), or specialized planners like the MARIO system are used (Bouillet et al. 2009), as a lower level analog to the higher level strategic planning problem. In this work, we seek to create an integrated system that marries lower-level planners like MARIO – which deal with one step of analysis at a time – with automated planners to conduct multi-step investigations that assist administrators and other stakeholders. In particular, we consider the problem of administering
a large network infrastructure with an eye towards security. Networks are typically monitored by a set of network administrators - humans who have experience with that network’s setup and can recognize the various types of traffic coming in and going out of the topology. These admins often have a highly complex model of the data flow profiles in the network at any given time. They call upon this experience in order to identify and isolate anomalies and extreme behavior which may, for example, be indicative of malware infections or other undesirable behavior. The process of analyzing these anomalies is christened an ‘investigation’, and involves a complex series of actions or decisions that are inter-dependent. These actions together form the model of the domain that resides within the expert, and that is applied to the incoming data. There are also a number of intermediate results from the world in the form of new, streaming data that must be sensed and accommodated into the on-going investigations. Finally, there are cost, duration and quality tradeoffs to the various decisions that the admins make. The aim of the strategic planning problem is to take in a model of this application as seen by the experts, and to produce decisions that will help the admins take actions that ensure the achievement of the scenario goals.

The main contributions of our work are constructing, and then solving, this strategic planning problem. First, we describe the various characteristics of the strategic planning problem, and then present a solution that enables the generation of faster decisions and decision-sequences. After that, we describe the model of the domain that we came up with, and its various characteristics and properties. Finally, we present the novel integrated system that we created to situate the plans produced using the model, and to solve the strategic planning problem end-to-end. We then evaluate our system with different automated planners, both in a real-world setting using six months of network data captured from a medium size network, as well as using a novel simulator we created to test the scalability of the underlying planners.

2 Planning Methods for Strategic Planning

The field of automated planning has seen a great deal of progress in the past decade, with advanced search heuristics contributing to faster and more efficient plan generation techniques. Concurrently, the complexity of features that can be supported representationally by planning methods has also increased. Where previously planners could only handle simple classical planning problems, they now offer support for time, cost, and uncertainty, to name a few important factors. These issues are important to us, since our model of the application domain (Section 3) and evaluations (Section 5) consider various problem scenarios that include all these features. The strategic planning problem that we are interested in solving is deterministic in many ways - the duration and cost of analytic applications that evaluate the data can often be estimated with fairly good precision. However, the analytics must run on real data from the world; this is the root cause of uncertainty in the strategic planning problem. Depending on the state of the world, and the data collected, the analytics may return one of many possible results. These results then have an impact on further planning. For example, in the network security scenario that we applied our work to, analytics influence the course of an investigation by labeling sets of hosts with certain properties. These properties cannot be ascertained until runtime, when the data from the world is gathered and given to the decision model that is being used in the strategic planning process. Since the decisions that are chosen at a given point can influence planning in the future, it is impossible to construct an entire plan beforehand.

Automated planning has had to grapple with this problem in the past, and solutions have been proposed to deal with the uncertain outcomes of actions. Incremental contingency planning methods (Dearden et al. 2003) solve this problem by building branching plans. In our application domain, however, the sensing actions can introduce new objects into the world model, which makes planning for all contingencies in advance difficult, if not impossible. More general approaches have been developed for modeling uncertain action outcomes, such as POMDPs (Kaelbling, Littman, and Cassandra 1998). We found that these approaches are not directly applicable in our setting, mainly due to the difficulties in maintaining reasonably accurate distributions. Instead, we needed a system that would eventually analyze all anomalies, however insignificant, as long as they have been flagged by the sensing actions.

In our case, one of the more prominent features of the strategic planning problem proves to be a saving grace: strategic planning proceeds in repeating rounds, viz. distinct stages composed of the following steps until the problem goals are met:

1. Data is gathered from the world via streams.
2. The best decision to make based on that data is chosen.
3. Analytics are deployed on that data based on the decision chosen.
4. The results of the analytics change the world and produce new data; back to step 1.

For a given round, a selected fragment of the plan is used to determine the next action given: (1) the data that is currently available; and (2) the overall problems goals (which typically do not change between rounds). Once the decisions from that plan fragment are available, we can treat the problem as a deterministic problem with costs and durations, since the only source of uncertainty is the results of the analytics that will be applied; and those analytics only contribute data to the next round of planning. In some sense, this can be seen as a determinization of uncertainty from the world that is afforded by replanning. The analytics that are deployed are really sensing actions, in that they initiate sensing in the world to bring in new data (world facts). By replanning at the beginning of each new round, the uncertainty that comes in with the data from the world can be dealt with, and the best plan based on all the information currently known can be generated. This plan is only executed
up until the next sensing action (analytic), upon whose execution the world changes and replanning is employed again. This method takes inspiration from previous successful approaches such as FF Replan (Yoon, Fern, and Givan 2007) and Sapa Replan (Talamadupula et al. 2010), which show that a combination of deterministic planners and replanning can be used as an efficient stand-in for contingency methods. An important part of such a technique, however, is the domain model used—a subject that we explore in the next section.

3 Domain Modeling

Hitherto, the large scale automation of data-processing systems has been handled by the creation of large inference rule-bases. These rules are usually put in place using information obtained from domain experts, and are applied to data gathered from the world in order to come up with inferences. However, such rules do not accommodate the concept of optimization when it comes to choosing which ones to apply. Given a specific state of the world, all of the rules that can possibly be applied will fire, regardless of whether or not that application is beneficial to the problem objectives and metrics. Inference rules are also cumbersome to specify, and hard to maintain. Due to the nature of the inference procedure, each new rule that is added to the base must first be checked for consistency; this means evaluating it against all the rules that are currently part of the rule-base, and ensuring that the introduction of this new rule does not produce a contradiction. Instead, a more declarative representation that can capture expert knowledge about the domain in question is a pressing need.

For the reasons specified above, we decided to use automated planning methods and the PDDL representation used by that community while modeling our network administration application. The former allows the optimization of decisions based on the current world state and specified metrics, while the latter is a declarative representation. Our main application was a network monitoring scenario where network data is being monitored for abnormal activity by administrators. The structure of the network being monitored is assumed to be finite and completely known to the admins, and various combinations of analytical tools (known as analytics) may be deployed by these admins to measure different network parameters at any given time. For ease of monitoring and classification, the network structure is broken down into constituent hostsets, where each hostset consists of one or more hosts. At an elementary level, a hostset may contain just a single host, which is a machine on that network that has an IP address associated with it. The process of identifying anomalies proceeds in the following steps:

1. Apply an analytic application (a combination of analytics) to a hostset
2. Break that hostset down into subsets to be analyzed more in-depth, based on the result of the applied analytic
3. Report a hostset if it sufficient analysis steps indicate the attention of a network admin is necessary
4. Repeat until there are no hosts / hostsets left

The decision pertaining to which analytics should be applied to which hostset is usually left to the network administrator, and their model of the network as well as prior experience in dealing with anomalies. It is this decision-making process that we seek to capture as part of our declarative model of this domain.

3.1 PDDL Modeling

After consulting with domain experts, we reached a consensus on the format of these decisions: each decision consists of a set of conditions that must hold (in the data) for that decision to be applied, and a set of changes that are applied to the data upon the application of that decision. This is very close to the STRIPS (Fikes and Nilsson 1972) and PDDL (McDermott and others 1998) model of an ‘action’. The first task in this pursuit was to elicit - from domain experts - the list of objects in this application, as well as the boolean predicates that model relationships between these objects. In our application, we had 8 different types of objects: some examples are hostset, which has been introduced previously as a collection of one or more hosts\textsuperscript{1} protocol, which indicates the network protocol in use (e.g. HTTP); and distancefunction, which denotes the kind of function used to measure the similarity between different hostsets or the distance between some behavior of a host and the aggregated model of behavior across the network.

Modeling the predicates was a more time-consuming task, since we had to identify the exact relationships between the objects, and how these relationships connected the objects in the world to the decisions (actions) that needed to be taken when looking for anomalies. A large number of the predicates in the final version of our PDDL model were unary predicates that indicated whether a certain characteristic associated with a hostset was true in the current state: for example, (extracted-blacklist ?s - hostset) indicates whether we know the set of blacklisted (malware) domains the hosts in the set s have contacted. In addition to these unary predicates about hostsets, we had some n-ary predicates (n > 1) that related a hostset to other objects in the model, like distance functions and protocols. We also had some ‘meta’ predicates, which were used for book-keeping purposes. An example of this is (obtained-from ?s \_ hostset), which indicates that hostset $s_1$ is refined from the larger hostset $s_2$ directly, in one step through the application of some analytic process. Finally, we had some 0-ary predicates, i.e., predicates with no parameters, to denote things that were true globally—e.g. (checked-global-frequent-hosts).

The list of decisions (or actions) was arrived at by having domain experts run through some usecases, and identifying the decisions that they took to label a hostset as exhibiting anomalous behavior that needed to be escalated up to an admin. Once we had a list of such decisions, we tried to determine the decisions that are required to go from the standard initial state—a giant hostset that contains all the hosts in

\textsuperscript{1}We do not consider the hosts themselves as individual entities, in the interests of scalability and efficient planning.
the network – to one where a specific (and very small) descendant of the initial hostset is reported as anomalous. This enabled us to construct a causal graph \( \Gamma \) of the domain theory as encapsulated by the network admins. In \( \Gamma \), the nodes stand for the decisions (actions) that the admins could choose to perform – remember that each decision corresponds to an analytic process or flow – and the edges denote a causal relationship between two actions. More formally, if actions \( a_1 \) and \( a_2 \) are related such that \( a_1 \) contains an add effect \( e \) which is present in the condition list of \( a_2 \), then \( \Gamma \) will contain a directed edge from \( a_1 \rightarrow e \ a_2 \) between those two nodes respectively.

Subsequent to the construction of \( \Gamma \), a clearer picture of the domain dynamics emerged. We found that there were some initial ‘setup’ actions that every hostset had to be subject to, in order to gather, filter and aggregate data for the analytics that would follow. There were 8 such actions in total, and the overall task of these actions was to group the hostsets and subnetworks by protocol. The last action in this sequence was a sensing action – sense-gather-final-protocols – that sensed the data from the network streams and split the initial (single) hostset into multiple hostsets, depending on the protocol that the individual hosts in the initial hostset exhibited anomalies on. In our domain, we considered three protocols that network data was being transmitted and received over: HTTP, generic TCP, and SMTP\(^2\). Thus, after the execution of sense-gather-final-protocols, the graph \( \Gamma \) splits into three different branches: one for investigating anomalies along the three different protocols mentioned above. On each one of these protocol-dependent paths, there are more regular actions which process the data contained in the hostsets. There also further sensing actions, which are decisions whose outcomes are uncertain and resolved in the world via the procedure described in Section 2. The three different branches merge into the last action of the causal graph \( \Gamma \), viz. pop-to-admin: this action pops-up the refined hostset at the end of the three branches to the network administrator for further review and action, thus fulfilling the planner’s role of offering suggestions to the human experts while cutting down on the size and complexity that they have to deal with.

**Advanced Features:** Once the causal structure of the domain model was established, we turned our attention to other domain characteristics that are important to a real world application: time, and cost. Modeling time is essential because many of the analytics that form the backbone of the decisions suggested by domain experts and/or the planner take time to execute on real data, and this needs to be taken into account when generating sequences of these decisions. Fortunately, PDDL offers support for temporal annotations (Fox and Long 2003), and we were able to extract estimates on action execution time from domain experts. Minimizing (or in some way optimizing) the makespan of plans for dealing with network anomalies is an important problem in industry, because it enables network admins to more quickly focus their attention on pressing problems that may infiltrate or take down an entire network infrastructure. A similar situation exists with cost – different analytic processes incur different computational costs when run, and it is useful to find a sequence of decisions / analytics to run that costs the least while still aiding the network admins in detecting anomalies. Since PDDL supports metric planning, with costs as well, we obtained cost estimates for each of the actions from the network admins and annotated the actions with these. We then ran the data and problem instances thus generated with a minimization on the ‘total-cost’ function as defined by PDDL.

### 4 Integrated System

The domain model described in the previous section can be used with any automated planner that supports the PDDL representation in order to devise plans that can identify anomalies in given sets of hosts. However, that automated planner must be part of a larger integrated system that can process data from the world, and that can effect the decisions that the planner suggests back in that dynamic world. The object of the novel integrated system that we designed around an automated planner was two-fold: (1) to translate the decisions that are generated by the planner after taking the scenario goals and metrics into account into analytics that can be run on streaming data from the world; and (2) to translate the results of analysis in the world back into a format that can be understood by the planner. The purpose of these two objectives is to enable the strategic planning rounds, defined in Section 2.

The schematic of our integrated system is presented in Figure 1. The PDDL model described in Section 3, along with the initial description of the specific problem (hostset) under investigation, are fed to the automated planner. This results in a plan being generated and passed through the **plan container**. The decisions that were generated as part of that plan are then handed to the **tactical planner**, which decides

![Figure 1: The integrated system that solves the strategic planning problem.](image-url)
which analytics to use to implement those decisions. The analytic processes are then scheduled and executed on underlying middleware platforms. The results of this execution – in the form of changes to the world – are passed back on to the metadata store, which is a module that stores all of the data related to the problem instance. This data is then piped through the state manager, which translates it to a representation that can be processed by the automated planner module. In this manner, the strategic planning loop is set up to support the various rounds. In the following, we describe each component of the integrated system - along with the role it performs - in more detail.

4.1 Automated Planner

The automated planner is the central component of our integrated system, since it enables the strategic planning process by generating intelligent, automated decisions based on data from the world. As discussed in Section 3, the automated planner must support certain advanced features in order to deal with a real world application scenario like network administration. Since this scenario had both temporal and metric issues associated with it, we decided to use two planners that are well known for handling these issues. We created two distinct instances of the domain model from Section 3; one that took cost issues into account, and another that considered temporal factors such as the time taken to execute each action.

FF Planner: In order to generate plans from the metric version of the domain, we chose to use the metric version of the Fast-Forward (FF) planner (Hoffmann 2003). FF has been used very successfully in the automated planning community for the past decade, and can be run with a number of options that direct the search process of the planner. The one that we found most pertinent to our system was the ‘optimality’ flag, which can be set (by default, it is turned off). FF also keeps track of and outputs relevant statistics when a plan is generated, like the number of search nodes that are generated and expanded. This is helpful when measuring the amount of planning effort required against problem instance and goal-set size.

LPG Planner: We used the Local Plan Graph (LPG) planner (Gerevini, Saetti, and Serina 2003) to generate temporal plans from the version of the domain that was annotated with execution times on the various actions. LPG is based on a local-search strategy, and can return temporal plans (which may or may not be optimal with respect to the duration of the resulting plan) in extremely short amounts of time. This suited our application, since we needed a quick turnaround on plan generation, and the plan quality itself isn’t an overriding consideration because of our plan-sense-replan paradigm. Along with the generated plan for a given instance, LPG also returns information such as the makespan (duration) of the plan, and the start times of each action.

Plan Container: Once the respective planners generate a plan that is appropriate for a given strategic planning round, that plan needs to be parsed into a form that can be handed over to the tactical planner and further on through the integrated system. The important components that we parse out of a generated plan, for each action, are: (1) the action name / label; (2) the parameters, or objects, that instantiate that action instance; (3) if the plan (and planner) is temporal, then the meta-information that deals with the duration of that action, and the time that the action is supposed to start executing. This information is parsed via a specific parser that is unique to each planner. The information is then stored in data structures so that it may be accessed by other components as required. The plan container is also tasked with “remembering” plans from previous rounds and determining the differences (cancelations or new actions) to be taken as a result of the current round.

4.2 Tactical Planner

The actions selected for execution by the plan container are then passed to the tactical planner, which configures and runs analytics corresponding to these actions. More specifically, for each action, the tactical planner generates an analytic flow, and runs the flow to completion. The analytic flows are deployed and run on analytic platforms, e.g., IBM InfoSphere Streams and Apache Hadoop. As implied by its name, the tactical planner uses its own planning to configure the analytics and connect them into analytic flows. It first translates each action received from the plan container into a (tactical) planning goal, and generates a (tactical) plan, which it then translates into an analytic flow. In our system, we separated the tactical and strategic planners based on significant differences in action semantics. During an investigation, multiple high-level sensing actions may be executed, and the knowledge obtained by sensing may affect the plan of the investigation. The tactical planner creates data analysis plans for each action of the strategic plan. The resulting tactical plans include lower-level instructions for configuring analytics and data sources, and are never modified during the execution process itself.

MARIO: Our implementation of the tactical planner is similar to the MARIO (Bouillet et al. 2009) system. In particular, it accepts goals specified as a set of keywords (i.e., tags) and deployment parameters, and composes and deploys analytic flows that meet these goals. Like MARIO, our tactical planner also supports deployment of composed flows on a variety of platforms. In our experiments, all analytics were either stream processing analytics deployed on IBM InfoSphere Streams or on Apache Hadoop. We note that for the purposes of the experiments described in this paper, it may have been possible to build a system without a tactical planner – replacing it with a simpler analytic launcher mechanism instead. However, this would have required the manual wiring of each of the analytic flows corresponding to a strategic action.

Simulator: Our integrated system features a novel tactical planning simulator, whose objective is to simulate analytics for the automated planner and the larger strategic plan-
The idea behind designing and incorporating this simulator module as part of the integrated system was to push the boundaries of automated planning systems, and to generate progressively larger and more complex problem instances. One of the main aims of our work was to evaluate the best automated planners for different situations that systems are likely to encounter in real world data, and the simulator provides a way of quickly generating different kinds of real world instances to enable this. This module, we simulate the **sensing actions** that are at the core of the plan-sense-replan loop by randomly generating effects from a pre-determined set of possible effects (which can be obtained from domain experts). For example, a hostset under investigation can be anomalous with respect to one of three protocols; one of the simulator actions would thus be to assign such a protocol at random (according to a pseudorandom generator whose parameters can be set). The simulator then generates facts and objects that are relevant to such an assignment, and inserts them back into the world state. In this way, the simulator skips the actual scheduling of decisions for execution on the analytics platforms, and the subsequent gathering of data from the world, and provides a quicker way of testing different automated planners on various quasi-real instances.

### 4.3 Analytics Platforms

Analytics that implement sensing actions are deployed in a scalable computational infrastructure managed by distributed middleware. Generally, we aim to support Big Data scenarios, where large clusters of commodity computers can be used to process large volumes of stored and streaming data. One such middleware platform for Big Data is IBM InfoSphere Streams. For constructing historical models of behavior from network data, we typically use the Apache Hadoop platform, by implementing our analytics in Apache Pig.

### 4.4 Metadata Store

The metadata store is a module that stores information about the raw data coming in from the world, and the mappings from that raw data into the representation that the automated planner uses (hence the “meta” in its name). When the analytics that are scheduled by the tactical planner finish executing in the world, the results of these computations are published to the metadata store. The mappings between the various parameters are then utilized in order to interpret the changes in the world into a planner-readable form. These are then passed on to the state manager.

**State Manager:** The state manager accepts changes in the world that are passed on from the metadata store, and puts them into a format that can be used as input to an automated planner. The state manager is the last component in the plan-sense-replan loop: it turns a deterministic, single iteration planner into the center of a replanning system by creating a new problem instance based on the execution of the plan generated in response to the previous instance. The state manager also keeps track of the overall scenario goals, and whether they have been achieved - in which case the system’s work is complete.

## 5 Evaluations

We evaluated the integrated system and the domain we created for network data analysis on recorded data from an institutional network, covering a period of six months from January 1st 2012 through June 30th 2012. The data consisted of recorded traces for 19564 unique IP addresses from the network for the following protocols:

- DNS requests and responses from all machines.
- Netflow summaries of data going through the institutional firewall, sampled at 1%.
- IPFIX summaries of network traffic through the firewall, as well as internal to the network, sampled at 1%.
- sFlow (Sampled Flow) data, consisting of sample packets going through the firewall, sampled at 0.1%.
- Public information about blacklisted domains on the Internet from Google SafeBrowsing service and as well as from the Malware Domain Blacklist.

The total recorded data size, compressed, was approximately 342 GB. We replayed this data using the IBM InfoSphere Streams middleware, at the maximum possible replay speed. This resulted in a total execution time of approximately 76 hrs and 23 minutes, which includes strategic and tactical planning rounds, as well as the time taken for the planned analytic flows to execute on InfoSphere Streams and Apache Hadoop. Our network data analysis domain model is designed to perform a drill-down analysis of host sets with anomalous behavior (e.g., substantially higher amounts of traffic or traffic with a lot of geographically distributed external locations in a short period of time). The drill-down process is modeled in the planning domain to first identify relatively large sets of hosts that exhibit some anomalous behavior at a coarse level – for instance, by looking at the total amount of traffic – and then to progressively refine these sets into smaller and smaller subsets by performing more in-depth analysis – for instance, specific analyses based on particular protocols that are identified as contributing to the

### Table 1: Evaluation summary

| Data interval   | 1/1/2012 – 1/7/2012 |
|-----------------|---------------------|
| Data used       | DNS, Netflow, IPFIX, sFlow, external blacklists |
| Data size       | 342 GB compressed |
| Execution time  | 76h 23m 12s |
| Tactical planner| 49 Streams, 16 Apache Pig components; approx. 31000 analytic flow deployments |
| Strategic planner| 17280 rounds (plans) |
| Hosts           | 371/19564 unique IPs flagged, 390000 hosts set analyzed |

[http://pig.apache.org](http://pig.apache.org)

[https://developers.google.com/safe-browsing/](https://developers.google.com/safe-browsing/)
[http://www.malwaredomains.com/](http://www.malwaredomains.com/)
anomalous behavior. As a result, our strategic plans typically begin by considering all the hosts in the network, identifying subsets that “look” anomalous, then narrowing these down to subsets for which we can perform more specific analyses, until finally we arrive at a very reduced set of hosts which we use to inform a network administrator.

Each action in the strategic plan corresponds to a goal for a tactical planner, which puts together the necessary analytic components to achieve the analysis results for the corresponding step in the strategic plan. Consequently, we implemented a tactical planning domain where actions consist of analytic components which are put together by the tactical planner to generate code for either InfoSphere Streams or Apache Hadoop. Our tactical domain consists of 49 InfoSphere Streams components and 16 Apache Pig components. These can be combined in 87 different programs (generated from the corresponding plans), but for the purposes of our experiments, only 33 of these had strategic actions associated with them (but note that these can have runtime parameters, the number of possibilities is actually much greater). During our evaluation, the tactical planner deployed approximately 31,000 analytic flows.

**Timing:** We measured the total time spent for strategic planning, tactical planning (including compilation of generated code) and other integrated system components. The results are shown in Figure 2(a). The important thing to notice here is that the combined overhead of the integrated system accounts for 6.65% of the total execution time; hence it is negligible.

**Strategic planning:** We looked at a few measures related to the strategic planning process. First, we counted how many changes to the state of the world (and hence, reruns of the strategic planner) are typically required. From Figure 2(b), we can see that the number is relatively stable around 640 rounds per week of data. Some ups and downs are due to seasonal effects of network activity (e.g., day/night, week/weekend cycles), as well as expiration and rebuilding of network traffic models based on which we identify anomalous hosts. The same stability is evident in the plan sizes, which lie in a tight band around 120 actions (Figure 2(c)). We should point out that since we replan for every change in the state of the world, some of the actions during the replanning may already be running (their corresponding analytic flows are deployed); others may be speculative paths that require the execution of a sensing action to decide whether that path will indeed be taken or replanning is necessary. The true number of changes (canceling or deploying analytic flows for stopped or new strategic actions) on every replan averages to just 6.1. Finally, we have chosen a week at random (in this case, week 11) and plotted the plan sizes in Figure 2(e). This indicates some local jitter, but the trend is that of a stable plan size. We noticed that at this scale, there is no noticeable effect of typical activity cycles...
We found that 187 out of the 371 hosts flagged by our system and compared them to what was abnormal by our system and identified as anomalous at a coarse level versus the total size of the most refined subsets obtained up to that point. The results in Figure 3 show that typically a host set is completely analyzed within 14 – 15 rounds of strategic planning.

**Model Scalability:** Since one of the contributions of our work was the novel PDDL model of the network administration scenario that we developed, we decided to evaluate the scalability of that model on different planning systems. Such experiments also allowed us to observe the domain’s behavior independent of the other integrated system components (the experiments described previously). In order to produce these results, we generated problem instances of increasingly large sizes – where size is either one of (1) the number of initial hostsets, or (2) the number of goals in the problem instance. We then provided these problem instances, along with the domain model, to both the FF (metric version) and LPG (temporal version) planners. Additionally, we also ran a subset of the problem instances with the SPPL planner (Riabov and Liu 2006).

### 6 Conclusions and Future Work

In this paper, we presented the novel strategic planning problem for the automation of real world safety-critical applications and described the creation of a new PDDL model that captured one such domain related to network administration and monitoring. We then discussed the application of an integrated system centered around an automated planner’s decisions to this model and real problems from that network administration domain, and presented promising results on a real world network.

As demonstrated previously, our integrated system does a reasonable job of automating the strategic planning process. However, much remains to be done in terms of testing the full capabilities of the system. On the modeling side, we are currently looking at modeling other business applications that feature large amounts of streaming data as well as sensing actions. One such application that we have started modeling is data analysis for healthcare in an intensive care setting, where data is gathered from the various instruments that are deployed on a patient, and investigations must be launched based on existing medical theories as well as the histories of past patients. We are also looking to expand the capabilities of the integrated system in at least three major ways: (1) incorporate more automated planners into the system, so that we may choose the best one depending on the particular scenario and problem instance at hand; (2) create a comprehensive report on the performance of different automated planners under different problem instances; and (3) tuning the parameters of the underlying analytic processes automatically during execution.

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