Domain-independent Generation and Classification of Behavior Traces

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Abstract

Financial institutions mostly deal with people. Therefore, characterizing different kinds of human behavior can greatly help institutions for improving their relation with customers and with regulatory offices. In many of such interactions, humans have some internal goals, and execute some actions within the financial system that lead them to achieve their goals. In this paper, we tackle these tasks as a behavior-traces classification task. An observer agent tries to learn characterizing other agents by observing their behavior when taking actions in a given environment. The other agents can be of several types and the goal of the observer is to identify the type of the other agent given a trace of observations. We present cabbot, a learning technique that allows the agent to perform on-line classification of the type of planning agent whose behavior is observing. In this work, the observer agent has partial and noisy observability of the environment (state and actions of the other agents). In order to evaluate the performance of the learning technique, we have generated a domain-independent goal-based simulator of agents. We present experiments in several (both financial and non-financial) domains with promising results.

1 Introduction

Given some training traces obtained by observing at least two kinds of agents, the goal of this research consists of learning a classifier that can differentiate among those types of agents by observing traces of their behavior. We assume there is a, usually hidden, rationale for the behavior of agents when taking actions in the environment that depends on some (again hidden) goals and the states they encounter while taking actions to achieve those goals. And we also assume goals, states and actions can be represented using standard planning representation languages.

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We leverage on previous work on sequence classification in contexts where there was no domain model and the representation of traces was a vector of features [Xing et al., 2010]. Some of those approaches did a manual definition of the relevant features to be used in the classification, which usually resulted in domain-dependent approaches. And none of these approaches used a relational representation of data in the form of goals, states and actions. Instead, we assume the other agents use a hidden planning model and the relevant aspects to make the classification depend on the actions executed and the related states.

Given the setup of an observer agent and a planning-execution agent, several decision-making tasks can be defined. Within this setting, most works in automated planning have focused on goal/plan recognition, where the observer has to infer the goals the planning agent is pursuing [Ramírez and Geffner, 2010] or the plan it is using to achieve some goals [Avrahami-Zilberbrand and Kaminka, 2005]. Once the goals/plans are recognized, other planning-related tasks can be solved such as generating plans to stop an opponent to reach its goals [Pozancho et al., 2018] or change the environment to improve the goal recognition task [Keren et al., 2014]. Other uses of traces include learning action models [Aineto et al., 2019] or predicting the next action or sequence of actions another agent is going to perform [Bernard and Andritsos, 2019, Tax et al., 2017]. However, as far as we know, the sequence classification task has not been addressed yet within the planning community.

Even if it has been less studied than related tasks in the context of automated planning, many real-world tasks benefit directly from this research. Some of these domains have been studied in the context of domain-dependent approaches [Xing et al., 2010]. Examples are: predicting whether someone will buy a product from the web clicks sequence; detecting intrusions in network or stand-alone computer systems; classification of anomalous behavior in public spaces (e.g. terrorism); machines monitoring the behavior of other machines; or labeling an opponent’s behavior in a game. In the case of financial applications there are numerous examples of the use of this task such as: fraud or anti-money laundering detection; classifying malicious traders; attrition prediction; offering new services to customers; or detection of users that will complain.

We present as contributions: a learning technique that can classify in agents’ types based on their behavior expressed in observation traces; and a domain-independent simulator of agents’ behavior based on dynamic goal generation, planning and execution. We name the first contribution Classification of Agents’ Behavior Based on Observation Traces (CABBOT). Some of the simulator features are: explicit reasoning on goals generation, modification and removal; ability to inject new instances when needed; several methods for generating goals (goals schedule, behavior-based random generation); exogenous events; non deterministic execution of actions; and partial and noisy observability.

A version of this work was published in [Borrajo et al., 2020]. We focused before on its application to money laundering, while this paper focuses on its general applicability to planning tasks. Therefore, the description of the techniques and the simulator are centered on the underlying planning tasks, and the experiments report on several domains. Thus, we also present as contribution
several domains designed for this task, whose detailed description is included in
the experimental section. The domains range from a simplified terrorist domain
to a service cars domain and two financial services related ones. The results
show that CABBOT can accurately classify agents in those domains.

2 Background

Given that we assume agents’ rational behavior to be based on the concepts
of goals, states and actions, we will use the automated planning formalism to
describe the tasks we deal with in this paper [Ghallab et al., 2004].

2.1 Automated Planning

We use the standard classical STRIPS definition of a planning task, augmented
with numeric variables (functions). A planning task is defined as $\Pi = (F, A, I, G)$,
where $F$ is a set of boolean and numeric variables, $A$ is a set of actions, $I \subseteq F$
is the initial state and $G \subseteq F$ is a set of goals. Each action $a \in A$ is defined in
terms of its preconditions (pre($a$)) and effects (eff($a$)). Effects can set to true
the value of a boolean variable (add effects, add($a$)), set to false the value of a
boolean variable (del effects, del($a$)), and change the value of a numeric variable
(numeric effects, num($a$)). We will denote with $S$ the set of all states. A (full)
state is a valuation of all the variables in $F$: a boolean value for all the boolean
variables and a numeric value for the numeric ones. Action execution is defined
as a function $\gamma: S, A \rightarrow S$; that is, it defines the state that results of applying
an action in a given state. It is usually defined as $\gamma(s, a) = (s \setminus \text{del}(a)) \cup \text{add}(a)$
if pre($a$) $\subseteq s$ when only boolean variables are considered. When using numeric
variables, $\gamma$ should also change the values of the numeric variables (if any) in
num($a$), according to what the action specifies; increasing or decreasing the
value of a numeric variable or assigning a new value to a numeric variable. If
the preconditions do not hold in $s$, the state does not change.

The solution of a planning task is called a plan, and it is a sequence of instan-
tiated actions that allows the system to transit from the initial state to a state
where goals are true. Therefore, a plan $\pi = \langle a_1, a_2, \ldots a_n \rangle$ solves a planning task
$\Pi$ (valid plan) iff $\forall a_i \in \pi, a_i \in A$, and $G \subseteq \gamma(\ldots \gamma(\gamma(I, a_1), a_2) \ldots), a_n)$. In case
the cost is relevant, each action can have an associated cost, $c(a_i), \forall a_i \in A$
and the cost of the plan is defined as the sum of the costs of its actions:
$c(\pi) = \sum_i c(a_i), \forall a_i \in \pi$.

The planning community has developed a standard language, PDDL (Plan-
ing Domain Description Language), that allows for a compact representation of
planning tasks [Ghallab et al., 1998]. Instead of explicitly generating all states
of $\Pi$, a lifted representation in a variation of predicate logic is used to define
the domain (predicates and actions) and the problem to be solved (initial state
and goals).
2.2 Multi-Agent Framework

In this work we consider at least two agents: acting agent, C (e.g. bank customer) and observer agent, B (e.g. financial institution or bank). In order to create a realistic environment, we will consider that they have different observability of the environment. Thus, each one of them will have its own definition of a planning task, as it has already been defined in cooperative [Torreño et al., 2017] and adversarial [Pozanco et al., 2018] multi-agent settings. In the case of C, its planning task can be defined as $\Pi_C = \langle F_C, A_C, I_C, G_C \rangle$. In the case of B, we do not consider here its ability to plan.

B has a partial (public) view of C’s task. This view can be defined as $\Pi_{B,C} = \langle F_{B,C}, A_{B,C}, I_{B,C}, \emptyset \rangle$, where $F_{B,C} \subseteq F_C$, $A_{B,C} \subseteq A_C$, $I_{B,C} \subseteq I_C$ and the goals are unknown, represented as $\emptyset$. This view corresponds to the public part of those variables in other Multi-Agent Planning works [Torreño et al., 2017]. It also has a partial view of the initial state and the actions; since there will be some actions executed by C, or some preconditions or effects of those actions that B will not observe. B has no observability of C’s goals. This assumption contrasts with goal and planning recognition work that assumes a set of potential goals are known [Ramírez and Geffner, 2010]. In our case, this set would amount to all possible goals that can be defined given a domain (infinite in most cases). Finally, we relax previous works’ requirement on C rationality; C can generate optimal or sub-optimal plans.

As an example, a customer might have goals that are not observed by the financial institution, such as having committed a crime, or laundered money. Other goals will be observable only after the customer has executed actions within the financial system that might reveal them, such as having opened an account, worked for a company, made a money transfer, or withdrawn money from a bank. In relation to states, there will be information known by the customer that is not observable by the financial institution, such as how many hours the customer works, or products bought using cash. Similarly, some information will be known, such as products or services bought using financial instruments of the corresponding financial institution, or bills payed to utility companies. Finally, there will be actions performed by the customer that will not be observed by the financial institution, such as committing a crime, while others will be observable, such as making a money transfer.

Once C starts generating plans and executing the actions on those plans, B will be able to see: if the actions in $A_{B,C}$ are executed; and the components of the state related to variables in $F_{B,C}$. A planning trace $t_C$ is a sequence of states and actions executed by C in those states:

$$t_C = (I_C, a_1, s_1, a_2, s_2, \ldots, s_{n-1}, a_n, s_n)$$

where $s_i \in S_C$, $a_i \in A_C$. An observation trace is also a sequence of states and actions of C from the point of view of B $t_{B,C} = (I_{B,C}, a'_1, s'_1, a'_2, s'_2, \ldots, s'_{n-1}, a'_n, s'_n)$, where $s'_i \in S_{B,C}$, $a'_i \in A_{B,C}$. Each state $s'_i$ corresponds to the partial observability of C’s state $s_i$ by B. Also, each action $a'_i$ corresponds to either an action that can be observed from C, $a_i$, or a ficticious no-op action if $a_i$ cannot be
observed by $B$. There is no actual need of requiring the states to be part of the observation; given that $B$ has a model of $C$’s domain, $B$ can always reproduce the corresponding observable states, by simulating the execution of the observable actions. We will call $T_{B,C} = \{t_{B,C}\}$ the set of traces of agent $C$ observed by agent $B$.

In the classification task we are addressing in this paper, there are two $C$ agents we would like the learning system to differentiate by observing their behavior traces. As an example, consider a criminal and a regular customer. We want to address non-trivial learning tasks. Therefore, we assume there is nothing in the observable state that directly identifies one or the other type of $C$ agent. Nor there is any difference on the observable actions between the ones that can be executed by one or the other type of $C$. Formally, given two different types of $C$, $C_1$ and $C_2$, $B$’s observable information on both should be the same:

$$\Pi_{B,C_1} = \Pi_{B,C_2} = \langle F_{B,C_1}, A_{B,C_1}, I_{B,C_1}, \emptyset \rangle$$

3 Learning to Classify Behavior

$B$’s main task consists of learning to classify among the different types of $C$ (behaviors). The learning task can be defined as follows:

- Given: (1) a set of classes of behavior (labels) $\mathcal{C} = \{C_1, C_2, \ldots, C_n\}$; (2) a set of labeled observed traces $T_{B,C_i}, \forall C_i \in \mathcal{C}$; and (3) a partially observable domain model of each $C_i$ given by $\Pi_{B,C_i}$

- Obtain: a classifier that takes as input a new (partial) trace $t$ (with unknown class) and outputs the predicted class

A main requirement of cabbot is to be domain-independent. Therefore, we will not use any hand-crafting of features for the learning task. Another characteristic of this learning task is that it works on unbounded size of the learning examples. Traces can be arbitrarily large, as well as states within the trace and action descriptions (both in the number of different action schemas, and grounded actions). There is no a priori limit on these sizes. Using fixed-sized input learning techniques can be difficult in these cases and some assumptions are employed to handle that characteristic. Hence, we will consider here only relational learning techniques [Dzeroski and Lavrac, 2010], and, in particular, relational instance-based approaches [Emde and Wettchereck, 1996]. Relational learning techniques have been extensively used in the past to learn control knowledge [Veloso et al., 1995], or planning policies [Yoon et al., 2008, García-Durán et al., 2012], among other planning tasks [Jiménez et al., 2012]. But, as far as we are aware of, they have not been used for this learning task.

The key parameter of these techniques is the relational distance between two traces, $d: T \times T \rightarrow \mathbb{R}$. In order to define the distance between two traces, $t_1$ and $t_2$, we have several alternatives.
• Compute a distance between the sets of actions on each trace. A simple, yet effective, distance function consists of using the inverse of the Jaccard similarity function [Jaccard, 1901] as:

$$d_a(t_1, t_2) = 1 - \frac{|an(t_1) \cap an(t_2)|}{|an(t_1) \cup an(t_2)|}$$

where $an(t_i)$ is the set of actions’ names in $t_i$. This distance is based on the ratio of common action names in both traces to the total number of different action names in both traces.

• Compute distances between sequences of states differences. Given two consecutive states $s_1$ and $s_2$ in a trace, we define their associated difference or delta, that represent the new literals in the state after applying the action. They are defined as: $\delta_{s_i,s_{i+1}} = s_{i+1} \setminus s_i$. We can compute a distance between the sets of deltas on each trace by using the Jaccard similarity function as before.

$$d_\Delta(t_1, t_2) = 1 - \frac{|\Delta(t_1) \cap \Delta(t_2)|}{|\Delta(t_1) \cup \Delta(t_2)|}$$

where $\Delta(t_i) = \{\delta_{s_j,s_{j+1}} | \forall s_j, s_{j+1} \in t_i, 0 \leq j \leq n - 1\}$ is the set of deltas of a trace $t_i$. Again, we only use the predicate and function names.

• The two previous distances only consider actions and deltas as sets. If we want to improve the distance metric, we can use a frequency-based approach (equivalent to an $n$-grams analysis with $n = 1$). Each trace is represented by a vector. Each position of the vector contains the number of times an observable action appears in the trace. The distance between two traces, $d_g$, is defined as the squared Euclidean distance of the vectors representing the traces. As before, a new trace is classified as the class of the training trace with the minimum distance to the new trace.

• Instead of using only counts, the distance function can also consider actions and state changes as relational formulae and use more powerful relational distance metrics. We have defined a version of the RIBL relational distance function [Emde and Wettschereck, 1996] adapted for our representation of traces, $d_r$. We needed to adapt it given the different semantics of the elements of the traces with respect to generic RIBL representation of examples. Given two traces, we first normalize the traces by substitution of the names of the constants by an index of the first time they appeared within a trace. For instance, given the following action and state pair:

```plaintext
< create-account(customer-234,acc-345),
{acc-owner(customer-234,acc-345),
  balance(acc-345)=2000}>
```

the normalization process would convert the trace to:
This process allows the distance metric to partially remove the bias related to using different constant names in the traces. The distance $d_r$ is then computed as:

$$d_r(t_1, t_2) = \frac{1}{2}(d_{ra}(t_1, t_2) + d_{r\Delta}(t_1, t_2))$$

i.e. as the average of the sum of $d_{ra}$ (distance between the actions of the two traces) and $d_{r\Delta}$ (distance between the deltas of both traces). $d_{ra}$ is computed as:

$$d_{ra}(t_1, t_2) = \frac{1}{2} \sum_{a_i \in a(t_1)} \min_{a_j \in a(t_2)} d_f(a_i, a_j)$$

where $a(t_i)$ is the set of ground actions in $t_i$, $d_f$ is the distance between two relational formulas and $Z$ is a normalization factor ($Z = \max\{|a(t_1)|, |a(t_2)|\}$). We normalize by using the length of the longest set of actions to obtain a value that does not depend on the number of actions on each set, so distances are always between 0 and 1. $d_f$ is 1 if the names of $a_i$ and $a_j$ differ. Otherwise, it is computed as:

$$d_f(a_i, a_j) = 0.5 - 0.5 \frac{1}{|\text{arg}(a_i)|} d_{\text{arg}}(a_i, a_j)$$

where $d_{\text{arg}}(a_i, a_j)$ is the sum of the distances between the arguments in the same positions in both actions. Each distance will be 0 if they are the same constant and 1 otherwise. Again, we normalize the values for distances. Also, when two ground actions have the same action name, we set a distance of at most 0.5. For instance, if $l_1 = \text{create-account}(i1, i2)$ and $l_2 = \text{create-account}(i3, i2)$,

$$d_f(l_1, l_2) = 0.5 - 0.5 \frac{1}{2}(1 + 0) = 0.25.$$
since functions have numerical values, we have to use a different function $d_n$. In this case, each $l_i$ will have the form $f_i(arg_i) = v_i$. $f(arg_i)$ has the same format as a predicate (or action) with a name $f_i$ and a set of arguments $arg_i$, so we can use $d_f$ on that part. The second part is the functions’ value. In that case, we compute the absolute value of the difference between the numerical values of both functions and divide by the maximum possible difference ($M$) to normalize:\[d_n(l_i, l_j) = d_f(f_i(arg_i), f_j(arg_j)) \times \frac{\text{abs}(v_i - v_j)}{M}\]

We multiply both, since we see the distance on the arguments as a weight that modifies the difference in numerical values. For example, if $\delta_1 = \{\text{acc-owner}(i1,i2), \text{balance}(i2)=20\}$, $\delta_2 = \{\text{acc-owner}(i1,i3), \text{balance}(i3)=10\}$,

$d_r(\delta_1, \delta_2) = \frac{1}{2}(\text{min}\{0.25, 1\} + \text{min}\{1, 0.5 \times \frac{|20-10|}{M}\})$

Once we have a distance metric between traces, we use an instance-based technique, as $k\text{NN}$, to classify a new trace according to the $k$ traces with minimum distance, and computing the mode of those traces’ classes. Since the classifier takes a trace as input, CABBOT also allows for on-line classification with the current trace up to a given simulation step. A nice property of $k\text{NN}$ is that we can explain how a behavior was classified by pointing out the closest previous cases.

4 Generation of Synthetic Behavior

In real world applications, traces will come from observations of other agents’ actions. In this paper, we have also developed a simulator that can produce those traces for the $C$ agent. Figure 1 shows a high level outline of the simulator. $C$ takes actions in the environment by using a rich reasoning model that includes planning, execution, monitoring and goal generation. It is inspired in some planning and execution architectures [Guzmán et al., 2012], where the main difference lies on the dynamic generation of goals. In particular, the goal generation component allows the agent to change or generate new goals on-line as in past work on goal reasoning [Roberts et al., 2018].

The components of the simulator for the planning agents are: the $\text{Execution}$, that takes a domain and problem description and follows a reasoning cycle that involves generating a new plan by calling $\text{Planning}$, executing the next action(s) from the current plan in the environment and observe the next state, and obtaining new goals or state components from $\text{Goal generation}$. The simulator is domain independent, except for the Goal reasoning that needs to generate behavior corresponding to at least two types of agents in the same domain. Now, we present a description of each module.

$^1$We use a large constant in practice.
4.1 Execution

Execution performs several tasks for some iterations:

- if there is no plan, or there is a reason for replanning, it calls Planning to generate a new plan. Reasons for replanning include: the state received from the environment is not the expected one (it does not fully match the state predicted by the effects of the most recently action); and Goal generation has returned new goals and/or changes in the state. We are using a standard planner for replanning, but it can be substituted by replanning algorithms [Fox et al., 2006, Borrajo and Veloso, 2012].

- if there is a plan in execution, it selects the next action to execute and sends it to the environment. The environment simulates the execution of the action and returns a new state. As mentioned above, the new state can be the one defined by the effects (deterministic execution). Our simulator also includes the possibility of defining non-deterministic execution of actions, as well as the appearance of exogenous events.

- at each step, it also calls Goal generation for changes in the goals or partial descriptions of states, as explained below.

- the interaction with the environment also generates a trace of observations that will be used for both training and testing of the learning component of $B$. As explained before, the trace contains a sequence of actions and states from the point of view of $B$. Therefore, Execution applies a filter on both so that it only includes in the trace its observable elements. Observability is defined for each domain. We opted for a simplified way to define it as the sets of lifted actions and predicates that can be observed by $B$. Any ground action or state literal of a lifted action or predicate on those sets
will be observable. Besides, $B$ might not see the actual executed action but another one (noisy observations). Also, it might not be able to see some of the actions even if they are in the observable set (a further aspect of partial observability).

- each simulation finishes after a predefined number of simulation steps (horizon) that is a parameter, or after a plan has not been found in a given time bound. We set the time bound with a low value (10 seconds), since this is enough in the experimental domains we have used in most cases.

4.2 Goal generation

This component allows agents to generate believable behavior whose goals evolve over time depending on the current state of the environment. It takes as input the current problem description (state, goals and instances) and returns a new problem description. The first obvious effect of this module is to change goals. In order to do so, we have defined two kinds of behavior for each domain by changing the goals of each type of behavior. For instance, in the case of a terrorist domain, we define two types of agents: regular person and terrorist. The regular person would generate goals of going from one place to another. When the simulator has achieved the previous goal (moving to a place), this module will generate a new goal of being somewhere else randomly chosen. However, randomly, the knapsack that it carries might fall down and be forgotten by the person. So, when the person notices that it does not carry the knapsack, it will generate a new goal to hold it again. In the case of the terrorist, this module will randomly generate the goal of not carrying the knapsack. And even if it knows that it is not carrying the knapsack, it will not generate as goal to carry it again, as in the case of the regular person. As a reminder, the observer does not know the goals of the other agent.

This module can also change the problem state and instances. This is useful for generating new components of the state on-line, as with partial observability of a rich environment. Suppose, we want to simulate an open environment where agents wander around and go to places that were not defined originally in the initial problem description. One alternative consists of defining a huge state (and associated instances) in the initial problem description to account for the whole map. This forces the planner to generate many more instantiations than the ones actually needed to plan in the first simulation steps. The ability of Goal generation to change the state and instances descriptions, allows the simulator to generate new parts of the world (or even remove visited ones if not further needed) on the fly, making the process more efficient and dynamic.

4.3 Planning

We are working in a domain-independent setting. Therefore, domain and problem models are specified in PDDL. Thus, any PDDL complaint planner could
be used for this purpose. In particular, we are using some domains with extensive use of numeric variables (using PDDL functions). So, we are constrained to planners that can reason with numeric preconditions and effects. Examples of planners we are using are: LPG [Gerevini et al., 2003]; CBP [Fuentetaja et al., 2010], or SAYPHI [de la Rosa et al., 2013]. As expected, planners take as input a domain and problem description in PDDL, and return a plan that solves the corresponding planning task. All these planners generate sub-optimal solutions.

5 Experiments

We will first describe the experimental setting and then show and analyze the results.

5.1 Experimental setting

Due to the lack of existing domains in the planning community that address the task of behavior classification from planning-execution traces, we have defined several new domains:

- **terrorist**: a domain where people move around a grid that represents an open place (station, airport, square, ...) holding a knapsack. Regular people might accidentally drop the knapsack (with probability 0.2), but they try to recover it when they find out. Terrorists drop the knapsack (with probability 0.4) and leave it there. The model is composed of three actions (move, drop and take) and four predicates. The goal is to classify in terrorist or regular behavior from the observed traces. There is full observability in this domain, given that all actions and states are observable, and cannot differentiate between the two types of agents.

- **service cars**: some vehicles move around the streets of a city network. The model comprises seven actions and seven predicates. Actions include: moving from one street section to another connected one, boarding and unboarding a vehicle, stopping a vehicle and moving it again. The goal is to classify the vehicles that are particular cars from the service cars (taxis or equivalent). All actions and predicates are observed, except for two predicates (whether a driver of a car owns the car, and whether there is a passenger inside a service car or not). There are two board actions depending on the type of vehicle, but the observer cannot differentiate between the two. The same applies to debark actions. The probability a new goal related to moving someone appears is 0.6 in the case of service cars, while the probability a new goal related to moving the owner appears is 0.2 in case of private cars.

- **customer journeys (journey)**: customers access the mobile application of a bank and perform several operations. The model comprises 22 actions, 24 predicates and 2 functions. Actions include: logging in, checking or
changing diverse information on their accounts, or performing financial operations. The goal is to classify between customers that are active with the application from the ones that do not use it. The observable actions and predicates are equal for both types of customers. The main difference is the probability of a goal appearing at some point (need of a customer of performing some operation). Active customers will have a higher probability than non-active ones.

• **customer journeys (digital-journey):** another version of the previous domain, where the task consists of classification between digital users and traditional users. In terms of behavior, digital users have a higher probability of performing digital-based operations (such as quick payments) and traditional users tend to have a lower probability on those operations, but a higher one on traditional operations (such as paying bills).

• **anti-money laundering (AML):** customers of a financial institution perform operations such as money transfers, payments, or deposits. In the meantime, not observable by $B$, these customers are either involved in criminal activities, or are regular customers. The challenge in this domain consists of characterizing the type of behavior from observations related to standard activities with the bank. The model comprises 33 actions, 37 predicates and 12 functions. Actions include: criminal activities, getting a job, getting a payroll, or making financial operations. The goal consists of classifying between money laundering individuals and regular individuals. Observability is restricted to the information that a bank can have on a given customer. Therefore, predicates as someone being a criminal or getting dirty money are not observable, while predicates related to making transactions and opening accounts are. We have tried to make this domain rich in terms of the different traces generated by the simulator. Therefore, we have defined several probability distributions that affect issues such as probabilities of selecting different money laundering strategies by criminals, or buying different kinds of items by criminals and regular customers.

For each domain, we have randomly generated 10 traces of each type of behavior for training and 20 for test (where classes are uniformly randomly selected). We measure the accuracy of the prediction. We have used $k = 1$ for the experiments, given that we already obtained good results with that value. We have varied the following parameters to see the impact they have on the results:

• **length of the traces (simulation horizon).** We used the values: 5, 10, 20, 50 and 100. Default is 50.

• **similarity function.** We have used the defined ones: $d_a$, $d_\Delta$, $d_g$ and $d_r$. Default is $d_r$. 
• probability-goal-appears. We have defined a probability that a set of goals appear at a given time step. Once a set of goals appears, it might take several time steps to execute the plan to achieve all goals. In the meantime, we do not generate new goals, though the simulator is ready to work with that case too. We used the values 1.0, 0.8, 0.5, 0.1, 0.05 and 0.01. Default is 1.0.

We will present results by varying these parameters one at a time to observe the impact they have on the performance of CABBOT.

5.2 Results

Table 1 shows the results for the journey domain. In this domain, the behavior depends on the probability of a goal arriving for both types of customers: active and non-active. We varied those probabilities to analyze how their values affect the accuracy of CABBOT. We can observe that when the difference between the two probabilities gets smaller, the behavior becomes more similar (in terms of activity level of customers) and accuracy of classification degrades. In the extreme, when the two probabilities are equal – (0.5, 0.5) case –, the classification accuracy is equivalent to a random classification (0.55). We will use the combinations ⟨0.8, 0.01⟩ (named journey-B for bigger difference) and ⟨0.5, 0.1⟩ (named journey-S for smaller difference) for the remaining comparisons.

| Prob. active | Prob. non-active | 0.01 | 0.05 | 0.1 | 0.5 |
|--------------|------------------|------|------|-----|-----|
| 0.5          |                  | 1.00 | 1.00 | 0.85| 0.55|
| 0.8          |                  | 1.00 | 0.95 | 0.85| 0.70|
| 1.0          |                  | 1.00 | 1.00 | 0.95| 0.80|

Table 1: Classification accuracy in the customer journey domain varying the probability of appearing goals for the two kinds of customers, active and non-active.

The next results of the experiments are presented in Table 2. Rows represent the domains, and the columns are different lengths of the traces (horizons). The values correspond to the accuracy of CABBOT fixing all other parameters to their default values. The results show that CABBOT is able to correctly classify behavior traces in a high percentage of cases. We observe that we do not need a high number of traces nor lengthy traces to obtain good results. As expected, CABBOT had less accuracy in shorter traces, since it has observed less number of actions/states, so it is harder to correctly classify the behavior. In the case of the journey domain, the longer traces allow for more goals to appear in the case of non-active customers, making the classification harder. Also, as it was observed before, the results with a smaller difference of probability values
are worse than with a bigger difference, specially in the case of shorter traces’ lengths.

| Domain      | Length of traces |
|-------------|------------------|
|             | 5    | 10   | 20   | 50   | 100  |
| terrorist   | 0.60 | 0.90 | 0.95 | 1.00 | 1.00 |
| service car | 0.60 | 0.95 | 1.00 | 1.00 | 1.00 |
| journey-B   | 1.00 | 0.95 | 0.85 | 0.80 | 0.95 |
| journey-S   | 0.45 | 0.80 | 0.60 | 0.95 | 0.85 |
| digital-journey | 0.75 | 0.85 | 0.90 | 1.00 | 1.00 |
| AML         | 1.00 | 1.00 | 1.00 | 0.90 | 0.95 |

Table 2: Classification accuracy in different domains varying the length of the trace.

Table 3 shows the results when we vary the similarity function. As we can see, the accuracy is perfect in most cases for all domains except for the customer journeys one. Even if the intention when generating the two kinds of behavior was to include slight differences, the learning system is able to detect those by using the different similarity functions. In the case of the journey domain, we can see that the actions-based distance obtains better results than the one based on comparing goals. Since this domain has many different goals, when goals appear the traces differ more on the goals than on the actions achieving the goals. Also, the similarity function used does not affect much in this domain to differentiate between bigger (B) or smaller (S) probability differences.

| Domain      | Similarity function |
|-------------|---------------------|
|             | $d_a$ | $d_\Delta$ | $d_g$ | $d_r$ |
| terrorist   | 1.00  | 1.00     | 0.95  | 0.90  |
| service car | 0.50  | 1.00     | 1.00  | 1.00  |
| journey-B   | 1.00  | 0.50     | 1.00  | 0.80  |
| journey-S   | 0.75  | 0.50     | 1.00  | 0.95  |
| digital-journey | 1.00 | 0.95 | 1.00 | 1.00 |
| AML         | 1.00  | 1.00     | 1.00  | 1.00  |

Table 3: Classification accuracy in different domains varying the similarity function.

CABBOT can make on-line classification of traces as soon as observations are made. Table 4 shows the average number of observations before making the final classification decision when varying the similarity function. While in the AML and service car domains, it takes a small number of steps to make the final decision, the number of steps required in the other two domains is higher.
This is specially true in the case of the journey domain for the same reasons discussed above; i.e. goals could take some time to appear.

| Similarity function | Domain   | $d_a$ | $d_\Delta$ | $d_g$ | $d_r$ |
|---------------------|----------|-------|------------|-------|-------|
| terrorist           | 4.20     | 6.40  | 26.40      | 15.90 |
| service car         | 0.00     | 2.90  | 26.20      | 0.70  |
| journey-B           | 15.90    | 7.30  | 17.90      | 2.30  |
| journey-S           | 25.00    | 25.00 | 16.40      | 11.10 |
| digital-journey     | 2.80     | 10.60 | 10.55      | 5.90  |
| AML                 | 2.30     | 1.40  | 5.25       | 1.60  |

Table 4: Average number of observations before making the final classification decision when varying the similarity function in several domains.

Table 5 shows the results when we vary the probability of partial observability. We can see that when the probability of making an observation at a given time step decreases, so does the accuracy of the learning system and correspondingly the number of steps it takes the learning system to converge to the final classification increases. In the extreme, when the probability is 0.01 for a length of history of 50, the traces will at most consist of one or two elements, so classifying the traces becomes a hard task as shown by the low probabilities. The rate at which the accuracy decreases varies across domains. In the case of AML, digital-journey and journey-B domains, there is a slow decrease in accuracy. In the other three domains, the drop in accuracy is more acute starting at even a probability of observation of 0.5 in the terrorist domain.

| Probability of partial observations | Domain   | 1.0  | 0.5  | 0.1  | 0.01 |
|-------------------------------------|----------|------|------|------|------|
| terrorist                           | 0.95     | 0.45 | 0.50 | 0.50 |
| service car                         | 1.00     | 1.00 | 0.85 | 0.45 |
| journey-B                           | 0.90     | 0.90 | 1.00 | 0.60 |
| journey-S                           | 0.85     | 0.85 | 0.80 | 0.45 |
| digital-journey                     | 0.90     | 0.75 | 0.55 | 0.45 |
| AML                                 | 1.00     | 0.90 | 0.80 | 0.35 |

Table 5: Classification accuracy in different domains varying the probability of partial observability.

Table 6 shows the results when we vary the probability of an execution failure of individual action (degree of non-determinism). When an action fails, it stays in the same state. Since the length of the history is 50 steps, even if some actions fail, CABBOT is still getting enough observations to make accurate
Table 6: Classification accuracy in different domains varying the probability of individual action execution failure. In parenthesis, the number of steps until it converges to the final decision.

| Domain       | Probability of execution failure | 0.0  | 0.2  | 0.4  |
|--------------|----------------------------------|------|------|------|
| terrorist    |                                  | 0.95 | 0.90 | 0.80 |
| service car  |                                  | 1.00 | 1.00 | 1.00 |
| journey-B    |                                  | 0.90 | 0.95 | 0.95 |
| journey-S    |                                  | 0.90 | 0.95 | 0.80 |
| digital-journey |                              | 0.70 | 0.85 | 0.75 |
| AML          |                                  | 1.00 | 1.00 | 1.00 |

6 Related work

Given some sequence of events, there have been several learning tasks defined: sequence prediction (what the next step is going to be) [Bernard and Andritsos, 2019]; sequence generation (learning to generate new sequences, e.g. simulation); sequence recognition (determine whether the sequence is legitimate or belongs to a given type); sequential decision making (how to make decisions over time, e.g. planning). This paper deals with sequence recognition or classification.

This task has been addressed by using different types of techniques [Xing et al., 2010] based on: features, distances or models. Features can be the presence or frequency of k-grams for all grams of size k. Model-based assumes an underlying probabilistic model and learns the parameters (Naive Bayes, HMM, ...). In our case, the number of symbols in the alphabet is huge (if groundings), so computing conditional probabilities is intractable, or is very small (action schemas) and probably not useful. Otherwise, we would have to rely on domain knowledge to know, for instance, that the transaction amounts (not part of the actions) are relevant, or the sum of amounts of several consecutive transactions. So, we have opted to use a distances-based approach. Our learning task is also related to detecting anomalous behavior or outliers detection [Chandola et al., 2010, Gupta et al., 2013] where the techniques are the same ones. The main difference with respect to previous work is that their definition of traces is very simplistic in most cases: small number of action labels; no representation of state nor goals; and they do not handle relational data. From the point of view of classical automated planning, there has been related work on goal/plan recognition [Ramírez and Geffner, 2010]. However, as we discussed in the introduction, the task we deal with here is not about predicting the goal/plan, but about classifying a given behavior in a set of behavior classes.
We have used several similarity functions such as the ones based on Jaccard distance or RIBL. Other similarity functions have been defined in related tasks, such as process mining [Becker and Laue, 2012], plan diversity [Roberts et al., 2014] or plan stability [Fox et al., 2006] (see [Ontañón, 2020] for an extensive review). These previous similarity functions used mainly the actions in the plan, but did not include the corresponding states.

Some of our domains have been analyzed previously by similar approaches: understanding customer journeys in the field of marketing [Lemon and Verhoef, 2016]; predicting an on-line buy action from the sequence of clicks [Bertsimas et al., 2003]; process mining [van der Aalst, 2016]; intrusion detection in a computer network or system [Scholau et al., 2001]; or anti-money laundering [Lopez-Rojas and Axelson, 2012]. None of them used a representation based on planning tasks, nor any relational learning approach. So, their approaches relied on carefully selecting the features to be used for defining the learning examples.

7 Conclusions

We have presented four main contributions. The first contribution consists of posing the sequence classification task in terms of a richer representation framework than previous work. We use goals, states and actions to include the traces rationale in the traces description. The second contribution consists of a learning technique that takes a set of training traces of other agents’s behavior and can classify later traces in different classes. The third contribution is a simulator that generates synthetic behaviors where agents can dynamically change their goals, and therefore their plans. Execution of those plans is stochastic, so those agents are able to monitor the execution and replan when needed. Finally, the fourth contribution is a set of automated planning domains that can be used for comparison in future work. Experimental results show that this approach performs well in some domains, including variations of real finance-related domains.

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such jurisdiction or to such person would be unlawful. The authors thank Alice McCourt for her useful revision of the paper. The authors would like to thank Sameena Shah for her discussions on the applications of this work to the AML task. ©2020 JPMorgan Chase & Co. All rights reserved

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