PAMMELA: Policy Administration Methodology using Machine Learning

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Abstract: In recent years, Attribute-Based Access Control (ABAC) has become quite popular and effective for enforcing access control in dynamic and collaborative environments. Implementation of ABAC requires the creation of a set of attribute-based rules which cumulatively form a policy. Designing an ABAC policy ab initio demands a substantial amount of effort from the system administrator. Moreover, organizational changes may necessitate the inclusion of new rules in an already deployed policy. In such a case, re-mining the entire ABAC policy requires a considerable amount of time and administrative effort. Instead, it is better to incrementally augment the policy. In this paper, we propose PAMMELA, a Policy Administration Methodology using Machine Learning to assist system administrators in creating new ABAC policies as well as augmenting existing policies. PAMMELA can generate a new policy for an organization by learning the rules of a policy currently enforced in a similar organization. For policy augmentation, new rules are inferred based on the knowledge gathered from the existing rules. A detailed experimental evaluation shows that the proposed approach is both efficient and effective.

1 INTRODUCTION

In any organization, it is of utmost importance to ensure that all accesses to resources take place in an authorized manner. This can be facilitated by deploying an access control model. Over the years, several access control models have been proposed among which the Role-Based Access Control (RBAC) (Sandhu et al., 1996) model became quite popular as an effective means of access control. In spite of its widespread popularity, RBAC suffers from a major drawback of being unsuitable for dynamic and collaborative environments.

The Attribute-Based Access Control (ABAC) model (Hu et al., 2014) was proposed to overcome the limitations of RBAC. This model allows users or subjects to access resources or objects based on the attributes of the subjects, objects and the environment. Each attribute is assigned a value or multiple values from a pre-defined set of values for every subject, object and environmental condition. In order to deploy ABAC, a set of rules is required. A rule defines the required attributes and the corresponding permissible values for each attribute for a specific type of access. The set of all rules collectively comprise a policy. While determining whether to allow or deny an access request, the attributes of the requesting subject, requested object as well as those of the environment in which the access request is made are taken into account. If each attribute has been assigned a specific value as per some rule, then the access request is allowed, otherwise, it is denied. The process of creating a policy for implementing ABAC is known as policy engineering. This can be carried out in two ways - top-down (Narouei et al., 2017) and bottom-up (Mo-canu et al., 2015), (Xu and Stoller, 2015), (Gautam et al., 2017). Bottom-up policy engineering is also termed as policy mining. Combination of top-down and bottom-up approaches gives hybrid policy engineering (Das et al., 2018).
An organization intending to migrate to ABAC needs to design and implement an ABAC policy. Also, when an organization having an already deployed ABAC model, undergoes some changes, like opening of a new department or introduction of a new academic course, additional ABAC rules reflecting the changes need to be generated. Creating ABAC rules ab initio or completely re-mining an ABAC policy requires a considerable amount of administrative effort and time. These overheads can be substantially reduced if an existing policy is used as a reference for the creation of a new ABAC policy for migration. Also, instead of re-mining the complete policy in order to account for the organizational changes, it is more prudent to only create the additional rules. In both the scenarios, the existing ABAC policy can aid the process of creation of new ABAC rules, thereby effectively providing assistance in the task system administration.

In this paper, we propose a machine learning based methodology that will aid ABAC system administrators to efficiently augment an existing policy by including additional rules to accommodate various organizational alterations as well as to generate a new ABAC policy for an organization by referring to the existing policy of a similar organization. The key contributions of the paper are:

- We propose the ABAC Policy Inference Problem (ABAC-PIP) which takes as inputs an existing ABAC policy, a set of access requests and the attribute-value assignment information and creates a new set of ABAC rules that either augments the existing policy or constitutes a new policy. The rules thus created are considered as new since they are different from the existing ones in terms of certain attribute values.

- We propose a supervised learning based methodology for solving ABAC-PIP. We name our approach as Policy Administration Methodology using Machine Learning (PAMMELA). PAMMELA trains a machine learning classifier using an existing ABAC policy. The training includes both positive (rules that grant accesses) and negative (rules that deny accesses) rules. After training, PAMMELA creates a new set of access rules on being supplied with a set of access requests and attribute-value assignment information.

- We test our proposed policy inferring methodology on three manually crafted datasets that are created keeping in mind real-world scenarios. Our experiments show that PAMMELA shows promising results and provides a high degree of performance. We have experimented with a number of machine learning classifiers and show comparative results for all them.

It is to be noted here that the existing ABAC policy serving as a reference for the creation of the new rules is assumed to be correct and free from any form of inconsistency or noise. The reason is that the existing policy is assumed to have been deployed over a certain period of time and is considered to be a tried and tested means of access control enforcement.

The rest of the paper is organized as follows. Section 2 explores the different policy mining approaches present in the existing literature. In Section 3, we review the preliminary concepts related to ABAC. We formulate ABAC-PIP in Section 4 and present the corresponding solution strategy PAMMELA along with a discussion of the application scenarios in Section 5. Dataset description, evaluation metrics and experimental results are presented in Section 6. Finally, Section 7 concludes the paper with some insights into future research directions.

2 RELATED WORK

A considerable number of work has focused on developing techniques for creation of ABAC policies. Xu and Stoller proposed a strategy for mining ABAC policies from access logs (Xu and Stoller, 2014). Another work by Xu and Stoller has formulated the ABAC policy mining problem as an optimization problem and has presented weighted structural complexity as a policy quality metric (Xu and Stoller, 2015). Talukdar et al. (Talukdar et al., 2017) have proposed ABAC-SRM, a bottom-up policy mining method capable of creating generalized ABAC rules. Cotrini et al., in (Cotrini et al., 2018), have proposed Rhapsody, a policy mining technique that can handle sparse inputs and have defined a rule quality metric called reliability.

A scoring method for determining the quality of a policy and an attribute-based rule mining algorithm from the audit logs of an organization have been presented in (Sanders and Yue, 2019). This approach can minimize the under and over privileges for enforcing the principle of least privilege. The authors in (Alohaly et al., 2019) designed a methodology that can extract ABAC constraints in an automated manner from policies expressed in natural language. A constrained policy mining technique has been proposed in (Gautam et al., 2017). Lawal and Krishnan have proposed an approach for policy administration in ABAC via policy review (Lawal and Krishnan, 2021). Heutelbeck et al. (Heutelbeck et al., 2021) have designed a data structure for efficiently indexing policy documents and have proposed a method for finding the
relevant policy documents for a particular access request. Some recent works have combined ABAC with blockchain (Kumar et al., 2021), (Rouhani et al., 2021) and have explored the application of ABAC in smart healthcare (Zhong et al., 2021).

Several incremental and adaptive policy generation techniques are present in the current literature. Das et al. (Das et al., 2017) have proposed a policy adaptation strategy between similar organizations. They have formulated the NP-complete Policy Adaptation Problem (PoIAP) which aims at determining the value assignments of the attributes of each subject for a given ABAC policy and have proposed a heuristic algorithm for solving it. It can be noted that our proposed ABAC-PIP is different from PoIAP both in terms of the inputs and the output. Das et al. have further extended their work in (Das et al., 2019) by considering environmental attributes and hierarchical relationships among subject attribute values. Batra et al. (Batra et al., 2021b) have proposed an incremental policy mining technique that is capable of creating new ABAC rules when a new permission is added or deleted or a new attribute value is added or deleted. In (Batra et al., 2021a), the authors have presented a strategy for determining policy similarity, have proposed two methods for performing policy reconciliation and also presented a policy migration technique.

The rapid growth of artificial intelligence has spurred the application of machine learning in the field of access control. In (Mocanu et al., 2015), the authors have presented a policy generation technique using Restricted Boltzmann Machines. Karimi et al. in (Karimi et al., 2021b) have proposed an automated policy learning method from access logs using unsupervised learning by considering both positive and negative rules. (Jabal et al., 2020a) presents Polisma, a framework for learning ABAC policies from access logs by using a combination of statistical, data mining and machine learning algorithms. In (Karimi et al., 2021a), the authors have designed an adaptive policy learning method for home Internet of Things (IoT) environment using reinforcement learning. Jabal et al. have proposed an approach known as FLAP (Jabal et al., 2020b) for collaborative environments. FLAP enables one organization to learn policies from another organization and perform policy adaptation via a policy learning framework by using local log or local policies or local learning or hybrid learning.

In this work, we formulate a policy creation problem variant and name it as the ABAC Policy Inference Problem (ABAC-PIP). We employ machine learning algorithms for solving ABAC-PIP in order to generate ABAC rules. To the best of our knowledge, this kind of problem formulation and the design of end-to-end machine learning based solution strategy for aiding system administrators have not been addressed in the existing literature.

3 ABAC PRELIMINARIES

The ABAC model consists of the following components:

- A set $S$ of subjects. Each subject can be a human or a non-human entity.
- A set $O$ of objects. Each object corresponds to a system resource that should be accessed in an authorized manner.
- A set $E$ of environmental factors or conditions. Each condition can represent some temporal or spatial or some other kind of context in which a subject requests access to an object. For eg. location, time, etc.
- A set $SA$ of subject attributes. Each subject attribute represents a property associated with a subject and can assume a single or multiple values from a set of values. These values are known as subject attribute values. If a subject attribute assumes a single value, it is known as atomic valued. If it is assigned multiple values for a subject simultaneously, it is known as multi-valued. An example of a subject attribute is Department. The attribute value set of Department can include Computer Science, Electronics, and Mechanical.
- A set $OA$ of object attributes. All concepts mentioned for subject attributes are applicable for object attributes as well. An example of an object attribute is Type of Document and its possible values can be Project Plan, Budget, Expenditure Details.
- A set $EA$ of environmental attributes. All concepts discussed for subject attributes also apply for environmental attributes. Example of an environmental attribute is Time of Doctor’s Visit having possible values as Day Shift and Night Shift.
- A function $F_{sub}$ that assigns values to subject attributes for a subject. Formally, $F_{sub}: S \times SA \rightarrow \{v_s | v_s is a subject attribute value\}$. For eg., $F_{sub}(John, Department) = \{\text{Computer Science}\}$.
- A function $F_{obj}$ that assigns values to object attributes for an object. Formally, $F_{obj}: O \times OA \rightarrow \{v_o | v_o is an object attribute value\}$. For eg., $F_{obj}(File1.doc, Type of Document) = \{\text{Project Plan}\}$.
- A function $F_{env}$ that assigns values to environmental attributes. Formally, $F_{env}: E \times EA \rightarrow \{v_e | v_e is an environmental attribute value\}$.
• A set $P$ of permissions (operations). Common permission types can be read, write, update, execute, etc.
• A set $R$ of rules. Each rule specifies whether a particular type of access is to be granted or denied. A rule that permits an access is a positive rule and a rule that disallows an access is a negative rule. All the rules cumulatively constitute an ABAC policy. An example ABAC rule can be of the following form - $<\{\text{Department} = \text{Accounts}, \text{Designation} = \text{Accountant}\}, \{\text{Type} = \text{Payroll Data}, \text{Department} = \text{Any}\}, \text{view} >$. In natural language, this rule translates to - *If a subject belongs to the Accounts department and has a Designation of Accountant, then she can view the payroll data of any employee belonging to any department.*

4 ABAC POLICY INFERENCE PROBLEM

Designing ABAC policies is not a trivial task and requires a considerable amount of administrative effort. The overhead associated with the process of policy generation can be reduced if some existing policy serves as a reference point or guideline based on which new policies can be inferred. This observation is applicable for augmenting an existing policy database by incrementally adding new rules as well as creating a new policy for an organization that has a similar structure as that of another organization where ABAC is already deployed. In order to achieve this goal of aiding the policy administration process, we propose the ABAC Policy Inference Problem (ABAC-PIP).

ABAC-PIP takes a deployed ABAC policy, a set of subjects, a set of objects, a set of subject attributes and their corresponding values, a set of object attributes and their corresponding values and a set of access requests as inputs and produces as output, for each access request, the set of permissions $Pr$, associated with the access request if the access request is to be permitted or else the decision to deny the access request if it is not to be permitted.

The following underlying assumptions have been made for ABAC-PIP:

• The existing ABAC policy $P$ is correct and does not result either in any form of security breach or over-restrictive access decisions. The verification of the correctness of $P$ is under not the scope of the current work.
• The access requests present in the set $L$ are new access requests and the corresponding access decisions cannot be determined by the rules present in the already deployed ABAC policy $P$.
• The access requests contained in $L$ are derived from access logs of an organization and include both positive and negative access requests. Positive access requests are the ones which are to be granted and negative access requests are those which are to be denied.
• The new access requests are generated when an organization having a deployed ABAC model undergoes some changes which necessitate the creation of additional rules corresponding to the new access requests that will take place. An example of such a change can be the opening of a new department or the introduction of a new job designation.
• The new access requests can also be generated when an organization wishes to migrate to ABAC. This organization is similar in structure and workflow to another organization where ABAC has already been deployed.
• For the new access requests, the relevant information regarding the value assignment for the subject and object attributes are available.

In the following section, we discuss the applicability of ABAC-PIP to two policy administration scenarios and present the solution strategy that assists the corresponding policy administration tasks.

5 PROPOSED METHODOLOGY

We propose a machine learning based methodology for solving ABAC-PIP. Our approach is designed to help system administrators in creating ABAC policies and in the process, can reduce the overhead associated with policy creation. We name our proposed strategy as *Policy Administration Methodology using Machine Learning* (PAMMELA). In this section, we
first present a detailed overview of how PAMMELA solves ABAC-PIP and then elaborate on the scenarios where PAMMELA is applicable.

5.1 PAMMELA

PAMMELA is a supervised learning based methodology for solving ABAC-PIP. Our proposed strategy works in two phases. In the first phase, a machine learning classifier is trained using a set of labeled data. This labeled data is in the form of an ABAC policy consisting of several rules. Each rule defines the combination of the subject attribute-value pairs and the object attribute-value pairs for which a subject will be allowed to access and perform certain operations or acquire some permissions for an object. We refer to such rules as positive rules. The attributes are treated as features by the classifier. The positive rules help the classifier to learn under which conditions, an access request is to be granted and what are the corresponding permissions associated with the access.

In addition to this, it is also essential for the classifier to learn when an access request is to be denied. Such scenarios are covered by the negative rules. A negative rule specifies the attribute-value pairings for which an access request is not permissible. For negative rules, all those attribute-value pairs are considered which lead to unauthorized accesses, not just the ones which explicitly deny accesses. Such negative rules can be derived from the set of positive rules. If \( U \) denotes the set of all possible attribute-value pairings (both subject and object) and \( PR \) denotes the set of positive rules, then the set of negative rules \( NR = \{ U \} \setminus \{ PR \} \). Though it is straightforward to derive the elements of \( NR \), the task, however, is not trivial. The reason behind this is that, generally in any organization, the set of rules disallowing accesses is much larger in size than the set of rules allowing accesses. In PAMMELA, the machine learning classifier is also trained using the negative rules. In this case, the classifier learns to output denial as a decision. If the classifier is trained using only the positive rules, then when a negative access request is given as input to the classifier, it may not be able to output the correct decision. The reason for this is during the training phase, the classifier, in such a case, never learns to output a deny decision for the specific attribute-value combinations.

For supplying the input training data to the machine learning algorithm, we make use of categorical data. For each attribute value set, the categorical encoding starts increasing monotonically from 1 such that each subject or object attribute value is assigned a numerical value. For e.g., If we have a subject attribute \( \text{Designation} \) having values Assistant Professor, Associate Professor and Professor, then Assistant Professor can be assigned the value 1, Associate Professor can be assigned the value 2 and Professor can be assigned the value 3. If a particular attribute is not applicable for a certain subject or object, then a special value \( NA \) (for Not Applicable) is assigned as the attribute value for that subject or object. The reason for using categorical encoding is a reduced input vector size in comparison to the vector size that is obtained using one-hot encoding.

After training, PAMMELA generates new rules in the second phase which is the testing phase for the machine learning classifier. Here, a set of access requests is given as input to the classifier. The combinations of the attribute values present in these access requests are different from those present in the existing policy rules. Such new combinations of values can occur when either the subject attribute value set(s) or the object attribute value set(s) or both are augmented with additional values.

Both positive and negative access requests are given as input to PAMMELA in the second phase. Positive access requests are those which are to be granted and negative access requests are those which are to be denied. The reason for including both positive and negative access requests is that when the already deployed policy cannot account for the organizational changes, then any type of access request needs to be appropriately classified. We assume that for each of the new access requests, the relevant attribute-value pair assignment information are available. Based on the learning achieved in the first phase, the new access requests and the attribute-value information, PAMMELA classifies each access request by determining whether it is to be allowed or disallowed. If the access request is to be disallowed, PAMMELA outputs the decision \( NO \). On the other hand, if the access request is to be granted, PAMMELA outputs the set of permissions required to successfully execute the access request in addition to the decision of \( YES \). Once the relevant decisions have been derived, the newly generated rules are presented to the system administrator for inclusion into the policy database. The workflow of PAMMELA is depicted in Figure 1.

5.2 Policy Administration via Augmentative Policy Inference

Undergoing structural and functional changes is not uncommon for any organization. Examples of such changes include but are not limited to the following - (i) an organization can start a new department, (ii) an organization can introduce a new job designation, (iii)...
Figure 1: Block Diagram depicting the workflow of PAMMELA.

We elaborate the observations made above using the following examples. Suppose an XYZ university has two departments - Computer Science and Electronics. The university has deployed the ABAC model for access control. We consider one subject attribute User-Type having values Faculty, Student and Teaching-Assistant and one object attribute Resource-Type having values Question-Paper, Answer-Script, Assignment and Mark-Sheet. The university management decides to open a new department, Information Technology. The rules governing the access of the different resources by the users belonging Computer Science and Electronics, will no doubt be applicable for Information Technology. The new rules will have the Department attribute value as Information Technology. Another example can be that, if the Computer Science department wishes to introduce a new evaluation component, Quiz, then the rules for Quiz will be similar to those associated with the access of the existing component Assignment.

5.3 Policy Administration via Adaptive Policy Inference

When an organization intends to migrate to ABAC, a policy needs to be designed ab initio using a policy generation approach. The input to the policy creation process can be an access log consisting of a set of access requests. A considerable amount of administrative overhead associated with this task can be reduced if some already deployed ABAC policy is available which can serve as a guideline. Henceforth, we shall refer to this existing policy as reference policy and the new policy that is to be designed as target policy. Note that the structure of the organization where the reference policy is deployed is assumed to be similar to the structure of the organization that wishes to implement ABAC. In such a scenario, the rules present...
in the reference policy can be adapted to generate the
target policy. The adaptation process will handle the
dissimilarities present between the rules of the refer-
ence policy and the target policy in terms of the sub-
ject and object attribute values.

We explain the adaptive policy inference task using
an example. We take the example of XYZ university
mentioned in Sub-section 5.2 having two depart-
ments, Computer Science and Electronics. The sub-
ject as well as object attributes and their correspond-
ing values are the same as those mentioned in the pre-
vious sub-section. Suppose, another educational insti-
tute, PQR wishes to adopt the ABAC model. PQR has
two departments, Mechanical Engineering and Civil
Engineering. PQR has the same subject and object at-
tributes as those of XYZ. The subject attribute values
of PQR are also same as those of XYZ. For the object
attribute values, PQR has an additional value Presentation
aption component Presentation requires the same type of
accesses as that of Assignment. Thus the rules that
need to be implemented for PQR have the same struc-
ture as those of XYZ and hence, can be inferred by
taking the rules of XYZ as reference. In this way, the
reference policy of XYZ can be appropriately adapted
to create the target policy for PQR.

PAMMELA can effectively handle policy adap-
tation. The reference policy will serve as an input to the
machine learning classifier in the training phase. In
order to generate the target policy, the positive and
negative access requests present in the access logs
of the organization that wishes to implement ABAC
as well as the attribute-value assignment information
will be supplied to the classifier in the testing phase.
Based on the learning accomplished during training,
the classifier will output either a grant decision along
with the set of associated permissions or a deny de-
cision. This output combined with the attribute-value
assignment information will create the rules for the
target policy. One assumption in this context is that
the set of permissions associated with each rule of the
target policy is the same as that of a corresponding
rule of the reference policy.

Several recent works like (Das et al., 2017), (Das
et al., 2019), (Jabal et al., 2020a) and (Jabal et al.,
2020b) have addressed the problem of policy adap-
tation. The approaches proposed in (Das et al., 2017)
and (Das et al., 2019) do not make use of machine
learning. The techniques in (Jabal et al., 2020a) and
(Jabal et al., 2020b) use machine learning along with
a number of heuristic methods. To the best of our
knowledge, our proposed methodology PAMMELA
is the first end-to-end machine learning based stra-
gy for policy adaptation.

5.4 Discussion

PAMMELA offers the advantage of significant re-
duction of administrative effort for augmentative and
adaptive policy inferences by taking the ABAC rules
currently present in the existing policy database as
input. Needless to say that if these tasks are car-
ried out manually, it requires a huge amount of ef-
fort to painstakingly scan through the policy database
to determine which existing rules are most similar to
the rules that are to be created and generate the new
rules. This makes the entire process very time con-
suming and quite prone to errors. The tasks can be
accomplished using heuristic methods but at the cost
of designing several functions covering different sce-
cenarios and running several experiments to determine
the best possible strategy. If each strategy executes for
a considerable amount of time, then selection of the
most suitable approach will involve a lot of time over-
head even before the actual augmentation or adap-
tation process. PAMMELA eliminates all the above
mentioned issues by providing an end-to-end intelligent
solution for aiding system administrators. It is to
be noted that the rules present in the existing policy
are considered to be correct and consistent. Thus, the
scenario of any error present in the existing policy mi-
grating to the newly derived rules does not occur and
hence has not been considered in the current work.

6 EXPERIMENTAL EVALUATION

In this section, we discuss the datasets as well as the
metrics used for evaluating the performance of PAM-
MELA and then report the experimental findings.

6.1 Dataset Description

For the purpose of experimentation, we have manu-
ally created three datasets. Each dataset consists of
two parts - (i) an ABAC policy consisting of a num-
er of rules, and (ii) a set of access requests along with
attribute-value assignment information. The ABAC
policy is used in the training phase of PAMMELA
and corresponds to the existing or the reference pol-
cy. The set of access requests and the attribute-value
assignment information are used in the testing phase.

We have not used any synthetic dataset generator
or simulator for dataset creation. The datasets have
been created keeping real-world scenarios in mind so
that they are similar to actual physical organizations.
We have generated the set of subjects, objects, atomic
valued subject and object attributes and their corre-
sponding values in such a way that they mimic real-
Table 1: Attribute-value Count for Training Data.

| Attribute-Type | Attribute-Name | University Dataset 1 | University Dataset 2 | Company Dataset |
|----------------|----------------|----------------------|----------------------|-----------------|
| Subject        | Designation    | 3                    | 3                    | 12              |
|                | Post           | X                    | 6                    | X               |
|                | Department     | 4                    | 5                    | 5               |
|                | Course         | X                    | 120                  | X               |
|                | Degree         | 2                    | 2                    | X               |
|                | Year           | 4                    | 4                    | X               |
|                | Project-Name   | X                    | X                    | 6               |
| Object         | Resource-Type  | 7                    | 8                    | 8               |
|                | Department     | 4                    | 5                    | 4               |
|                | Course         | X                    | 120                  | X               |
|                | Degree         | 2                    | 2                    | X               |
|                | Year           | 4                    | 4                    | X               |
|                | Project-Name   | X                    | X                    | 6               |

life organizations. The rules as well as the access requests of each dataset are similar to actual organizational accesses and hence can be considered to be semantically meaningful. For each dataset, we have considered only one permission corresponding to the ability of a subject to access a given object or the denial of access. However, PAMMELA is capable of handling multi-permission scenarios as well. The datasets are:

**University Dataset 1:** We have designed this dataset to mimic the workflow of an educational institute.

**University Dataset 2:** Another dataset has been designed keeping in mind the structure and workflow of an educational institute and has been named as University Dataset 2. This dataset is much more detailed than University Dataset 1 both in terms of the attributes, their corresponding values as well as the number of rules present in the training data.

**Company Dataset:** This dataset has been created keeping in mind the structure and workflow of a software company and incorporates features and access rules similar to a real-life organization.

Table 1 shows the number of values associated with each attribute in the training data for a specific dataset. A ‘X’ in a table cell indicates that the corresponding attribute is not present for the dataset indicated by the column. Table 2 shows the number of rules present in the training data and the total number of as well as the number of positive and negative access requests present in the test data for each dataset. If a certain attribute is present in a dataset but is not applicable for a particular subject or object, then the value Not Applicable is assigned for that attribute.

Table 3 presents the number of new values introduced for the different attributes in the test data for the three datasets in the following format - attribute name: number of new attribute values. In the test data of each dataset, one new attribute value has been introduced in each access request.

6.2 Evaluation Metrics

The performance of PAMMELA is evaluated using the metrics of Accuracy, Precision, Recall and F1-score, as discussed below.

YES and NO respectively denote the grant and deny decisions given as outputs by PAMMELA. The terminologies and metrics are:

- **True Positive Accesses (TPA):** These are the positive access requests corresponding to which PAMMELA gives the output YES and are instances of correct classifications.
- **True Negative Accesses (TNA):** These are the negative access requests corresponding to which PAMMELA gives the output NO and are instances of correct classifications.
- **False Positive Accesses (FPA):** These are the negative access requests corresponding to which PAMMELA gives the output YES, i.e., misclassifications resulting in security breach.
- **False Negative Accesses (FNA):** These are the positive access requests corresponding to which PAMMELA gives the output NO, i.e., misclassifications resulting in an over-restrictive system.

**Accuracy:** It is the ratio of the correctly classified access requests to the total number of access requests. It denotes the capability of the classifier to make correct decisions. Mathematically, \[ \text{Accuracy} = \frac{TPA + TNA}{TPA + TNA + TPA + FNA} \]

**Precision:** It is the ratio of the correctly classified positive access requests to the total number of access requests for which the output is YES. Precision is inversely proportional to the degree of security breach occurring in the system. Mathematically, \[ \text{Precision} = \frac{TPA}{TPA + TPA + FPA} \]

**Recall:** It is the ratio of the correctly classified positive access requests to the total number of positive
Table 2: Training Data Rule Count and Test Data Access Request Count.

| Dataset              | Rule Count in Training Data | Access Request Count in Test Data |
|----------------------|-----------------------------|-----------------------------------|
|                      | Total | Positive | Negative | Total | Positive | Negative |
| University Dataset 1 | 53    | 1010     | 598      | 412    |
| University Dataset 2 | 156808 | 483      | 308      | 175    |
| Company Dataset      | 1616  | 287      | 95       | 192    |

Table 3: New Attribute Value Count for Test Data.

| Attribute-Type | Attribute-Name : New Value Count |
|---------------|-----------------------------------|
| Subject       | University Dataset 1               |
|               | University Dataset 2               |
|               | Company Dataset                    |
| Designation   | Designation : 2, Department : 5,  |
| Degree        | Degree : 2                         |
| Designation   | Designation : 1, Department : 1,  |
| Post          | Post : 1, Course : 21              |
| School        | Designation : 4, Project-Name : 1  |
| Object        | Resource-Type: 3, Department : 4,  |
| Degree        | Degree : 2                         |
|              | Resource-Type : 4, Department : 1,  |
|              | Course : 21                        |
|              | Resource-Type : 7, Project-Name : 1|

access requests. Recall is inversely proportional to the degree of over-restrictiveness of the system. Mathematically, $\text{Recall} = \frac{TP}{TP + FN}$.

- **F1-score**: It is calculated as the weighted average of precision and recall. F1-score balances the relative trade-off between precision and recall. It is calculated as $F1-score = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$.

### 6.3 Results

In this section, we present the experimental results. We have used the following machine learning classifiers to evaluate the performance of PAMMELA - Artificial Neural Network (ANN), Decision Tree (DT), Random Forest (RF), Extra Trees (ET), Gradient-Boosting (GB) and XGBoost (XGB). The implementation was done using scikit-learn library and the experiments were conducted on a MacBook Pro laptop having 2.3 GHz, 8 cores, intel core i9 processor, 16 GB RAM and macOS 11.4 as the operating system.

We report the performance of PAMMELA in terms of Accuracy (Acc), Precision (Pre), Recall (Rec) and F1-score (F1-s) in Table 4 for the three datasets.

The results show that PAMMELA provides the highest accuracy of 88.4% for University Dataset 1, 89% for University Dataset 2 and 88.2% for Company Dataset across all classifiers. The highest precision recorded for the University Dataset is more than 97% and is 86.7% for the Company Dataset. This implies that the number of misclassifications in terms of the false positive accesses is quite low. The recall achieved by our proposed approach is less than 90% for the University Datasets and less than 80% for the Company Dataset. This shows that PAMMELA can have a tendency to make over-restrictive access decisions which though not desirable but will not lead to security breaches. It should be noted here that our proposed methodology is designed to help system administrators in policy augmentation and policy adaptation. Instead of performing these administrative tasks either manually or heuristically, the system administrator can obtain the output from PAMMELA and manually inspect only a fraction of all the access requests that are misclassified. The accuracy, precision and recall values of Table 4 indicate that the misclassified access requests constitute only a small percentage of the entire access request set. Thus, it is evident that PAMMELA will accurately create majority of the rules and the administrator will need to manually create only a few rules, reducing the overall administrative effort to a great extent.

We next give examples of a few sample augmented rules generated by PAMMELA corresponding to each dataset. An example positive rule and an example negative rule of each dataset are listed below. Here, the common subject and object attributes are represented as Subject.Attribute – Name and Object.Attribute – Name respectively.

**University Dataset 1:**

- {Designation = Student, Subject.Department = Information Technology, Subject.Degree = BTech, Subject.Year = First}, {Resource-Type = Assignment, Object.Department = Information Technology, Object.Degree = BTech, Object.Year = First}, {Access = Allow}
- {Designation = Officer, Subject.Department = Accounts, Subject.Degree = NA, Subject.Year = NA}, {Resource-Type = Question Paper, Object.Department = Information Technology, Object.Degree = BTech, Object.Year = First}, {Access = Deny}

**University Dataset 2:**

- {Designation = Faculty, Post = Associate Professor, Subject.Course = Parallel Computing, Subject.Department = CSE, Subject.Degree = NA, Subject.Year = NA},
Table 4: Experimental Results.

| Classifier | University Dataset 1 | University Dataset 2 | Company Dataset |
|------------|----------------------|----------------------|-----------------|
|            | Acc | Pre | Rec | F1-s | Acc | Pre | Rec | F1-s | Acc | Pre | Rec | F1-s |
| ANN        | 0.730 | 0.971 | 0.560 | 0.710 | 0.890 | 0.951 | 0.873 | 0.910 | 0.763 | 0.667 | 0.568 | 0.614 |
| DT         | 0.864 | 0.932 | 0.831 | 0.879 | 0.716 | 0.758 | 0.815 | 0.786 | 0.882 | 0.867 | 0.758 | 0.809 |
| RF         | 0.880 | 0.969 | 0.824 | 0.891 | 0.706 | 0.928 | 0.584 | 0.717 | 0.871 | 0.815 | 0.789 | 0.802 |
| ET         | 0.884 | 0.969 | 0.831 | 0.895 | 0.737 | 0.979 | 0.601 | 0.744 | 0.857 | 0.793 | 0.768 | 0.781 |
| GB         | 0.881 | 0.935 | 0.860 | 0.895 | 0.489 | 0.604 | 0.575 | 0.589 | 0.777 | 0.696 | 0.579 | 0.632 |
| XGB        | 0.864 | 0.932 | 0.831 | 0.879 | 0.652 | 0.893 | 0.516 | 0.654 | 0.836 | 0.761 | 0.737 | 0.749 |

The training time for PAMMELA depends on the number of rules and the number of attributes present in the training data. The number of subjects and objects have no effect on the training time. We observed that for ANN, PAMMELA took approximately 130 seconds to complete the training on University Dataset 2. This is the highest recorded training time for our experiments. For the other classifiers, PAMMELA gave much lower training execution times on all the datasets. The reason for this is that the University Dataset 2 is the largest dataset in terms of the number of attributes and rules. The average testing time for PAMMELA was less than 1 second. Of course, the testing time is dependent upon the number of access requests considered. The train and test time indicate that experimenting with multiple classifiers will not be too time consuming. A system administrator can experiment with a number of classifiers for PAMMELA before selecting the best possible option. Once training has been done, PAMMELA can keep on generating new rules without any further training. However, if the policy used for training needs to be changed altogether (may happen if the organizational structure or workflow undergoes some radical modifications), then the classifier will need to be re-trained.

7 CONCLUSION

In this paper, we have proposed the ABAC Policy Inference Problem (ABAC-PIP) that aims to derive a new set of attribute based rules from an existing policy. We have proposed an end-to-end supervised learning based methodology, PAMMELA for solving ABAC-PIP. System administrators can use PAMMELA for augmentative as well as adaptive policy inference when an organization undergoes some changes or an organization migrates to ABAC by adapting the policy of a similar organization. Experimental results show that PAMMELA can be effectively used for aiding system administrators.

In the future, we intend to apply deep learning, reinforcement learning and incremental learning for inferring ABAC policies. Another direction of future research can be attempting to adapt the ABAC policies of multiple organizations for a single target organization. This will be a challenging task as it will require resolving the conflicts among the rules of different organizations.
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