Accuracy vs. Time Cost: Detecting Android Malware through Pareto Ensemble Pruning

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Problem

Malware poses a severe threat in our daily life due to the massive downloads of applications in recent years. Much progress has been made on the detection accuracy, but neglects the computational cost.

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We propose a malware detection system through Pareto ensemble pruning to trade off the classification accuracy and the computational cost.

Pareto Ensemble Pruning

The problem is formulated as a bi-objective optimization problem,

1. Obj: Classification accuracy;
2. Obj: Computational cost.

Let T_t denote a pruned classifier set with the selected vector $t \in \{0,1\}^m$, where $t_i = 1$ indicates the base learner b_i is selected for the ith component. The optimal pruned ensemble $T_{opt.sel}$ can be formulated as follows:

$$T_{opt.sel} = \arg\min_{t \in \{0,1\}^m} \; E(T_t) + w \cdot |T_t| \,,$$

where $E(T_t)$ is the validation error rate of T_t, $w \in [0, +\infty]$ is the trade-off level, and

$$E(T_t) + w \cdot |T_t|$$

is the combined loss function.
Given a validation dataset with k instances, for validation instance i, $T_t(x_i)$ is the prediction value of T_t, and y_i is the actual value. $E(T_t)$ is calculated as

$$E(T_t) = \frac{1}{k} \sum_{i=1}^{k} \chi\left(T_t(x_i) \neq y_i\right),$$

where $\chi(\cdot)$ is the indicator function, which equals 1 if the expression holds; otherwise, it equals 0. The size of the ensemble is computed as:

$$|T_t| = \sum_{i=1}^{m} t_i$$

The optimal pruned ensemble $T^{(i)}_{opt.sel}$ can be defined based on different trade-off levels w_i, for all i:

$$T^{(i)}_{opt.sel} = \arg\min_{t \in \{0,1\}^m} \; E(T_t) + w_i \cdot |T_t| \,.$$

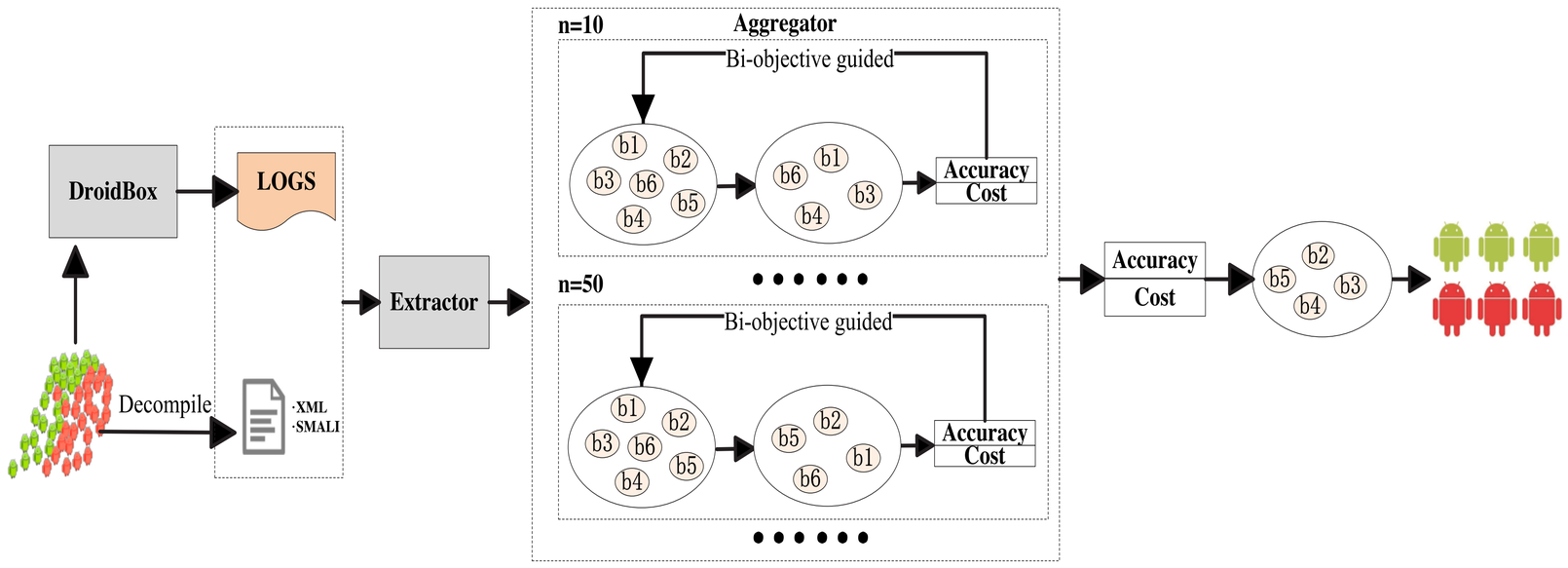
Features

We select 155 features in total to perform a binary classification. Four types of features are shown below:

Type of Features	Selected Features
Permission	59
Sensitive API Call	90
Sequence	1
Dynamic Behavior	5
Total	**155**

Begonia

Four steps: Reverse Engineering ⟶ Feature Extraction ⟶Ensemble Pruning ⟶ Classification

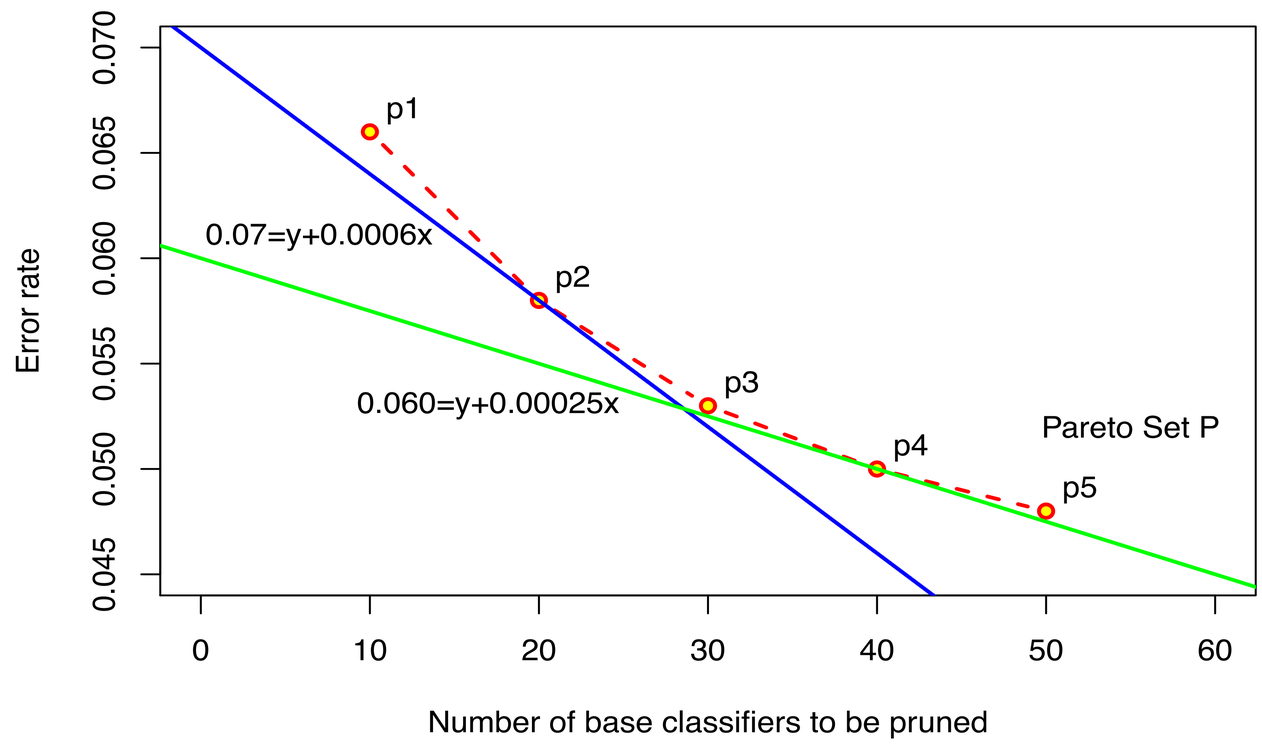


Optimal Ensemble Selection

To trade off the two objectives, provided by a trade-off level w, we select the final ensemble that minimizes the combined loss (*i.e.*, $E(T_t) + w \cdot |T_t|$), e.g., given different trade-off levels,

$$w_1 = 0.0006 \xrightarrow{\text{final ensemble}} p_2;$$

$$w_2 = 0.00025 \xrightarrow{\text{final ensemble}} p_4.$$



Results

Goal: To examine the relation between accuracy and time cost of real-time analysis.
Iteration times: $\lceil n^2 \log n \rceil$, when dealing with the bi-objective solver.

# Group Size	Time (sec)	Accuracy
10	60	93.40%
20	460	94.20%
30	1,546	94.70%
40	3,654	95.00%
50	7,450	95.20%

*Note that accuracy column indicates the highest accuracy of each group.

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