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Towards Explicable and Adaptive DDoS Traffic Classification

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Introduction & Background

- Decades of research and industry efforts have led to a myriad of DDoS detection and classification approaches. Nowadays, many researchers begin to harness machine learning in classifying DDoS attacks. However, such methods have two negative aspects:
  1. The prediction results are inexplicable. An unexplainable result may lead to unexpected collateral damage when conducting access control.
  2. Learning-based methods are not adaptive. A model trained in one environment cannot easily apply to another environment.

Introduction & Background

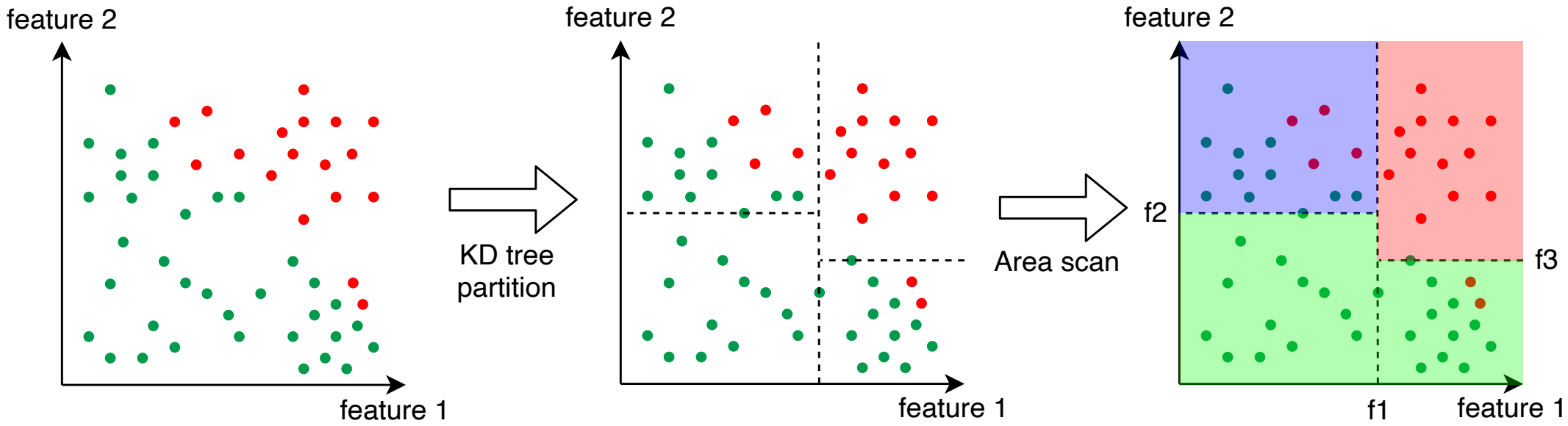
- In this poster, we propose a learning-based DDoS traffic detection and classification method.
  1. It utilizes a modified k-nearest neighbors algorithm to detect DDoS threats.
  2. It then conducts fine-grained traffic classification using risk degree sorting with grids.
  3. To improve efficiency, we use a k-dimensional tree to partition the searching space, shortening the time for queries significantly.
- Compared with the previous learning-based approaches, this method is highly explicable and adaptive.

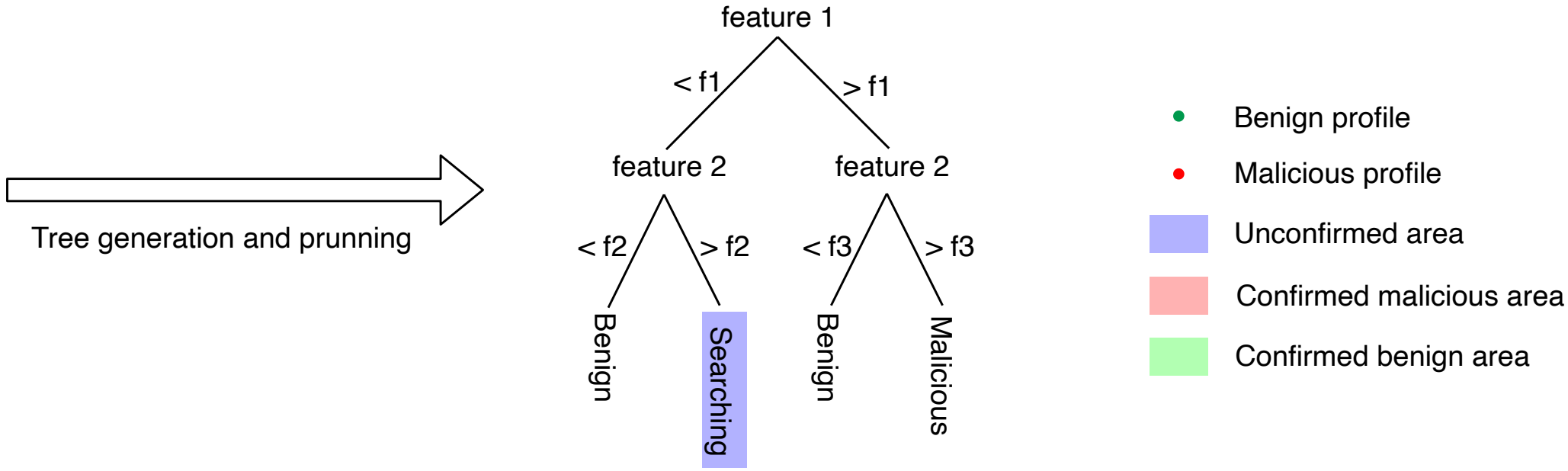
Methodology

- Our approach has two phases, which are DDoS **detection** and **classification**.
- It monitors the traffic in batches. Each batch *t* is a uniform time bin, which is also the most basic detection unit.
- During each batch *t*, our approach will extract features to form a traffic profile *S (S = { feature 1 , feature 2 , ..., feature n })* and input it into the detection module.
- In the classification phase, our approach will generate traffic profile *D (D = { feature 1 , feature 2 , ..., feature n })* for each source IP and determine whether it is malicious according to the features.

Phase one: detection of DDoS traffic

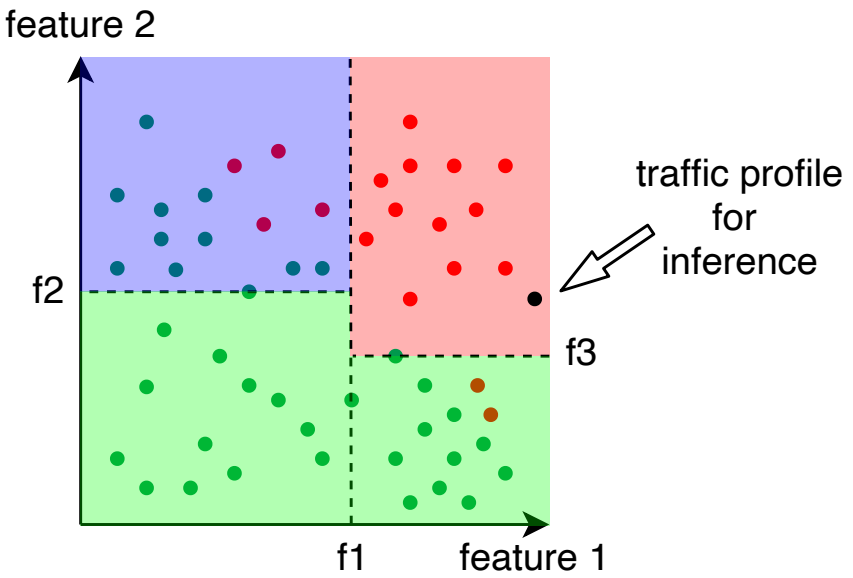
- We use k-nearest neighbors (KNN) algorithm in the detection of DDoS traffic.
- Although it takes no time to train the model, the prediction requires a time complexity of *O(nlogn)* to complete. Hence, we leverage the KD tree to partition the searching space, reducing the number of data points to enumerate.
- Furthermore, our approach generates a decision tree out of the KD tree, reducing the time complexity for traffic monitoring to nearly O(1).

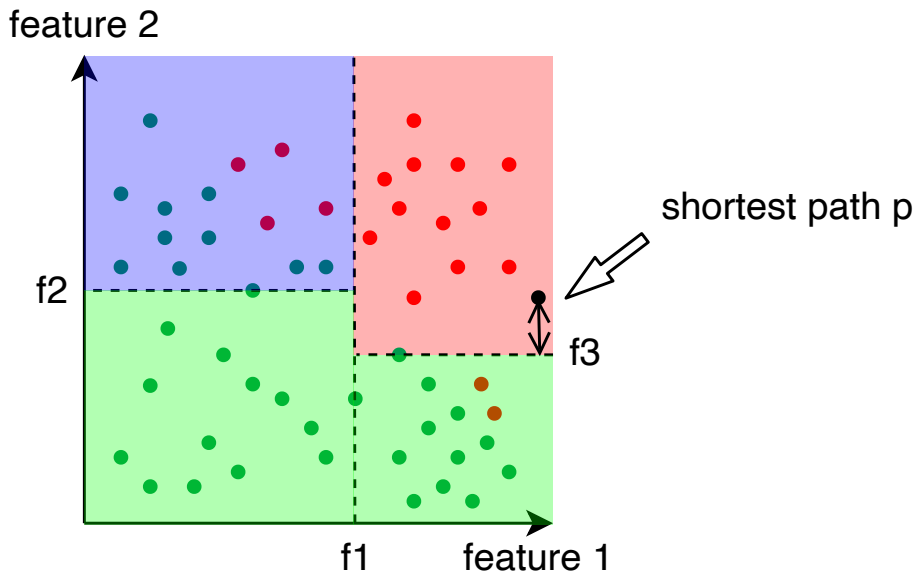

feature 2
feature 1
KD tree
partition
feature 2
feature 1
Area scan
feature 2
f2
f3
f1
feature 1


Tree generation and prunning
feature 1
< f1
> f1
feature 2
feature 2
< f2
> f2
< f3
> f3
Benign
Searching
Benign
Malicious
Benign profile
Malicious profile
Unconfirmed area
Confirmed malicious area
Confirmed benign area

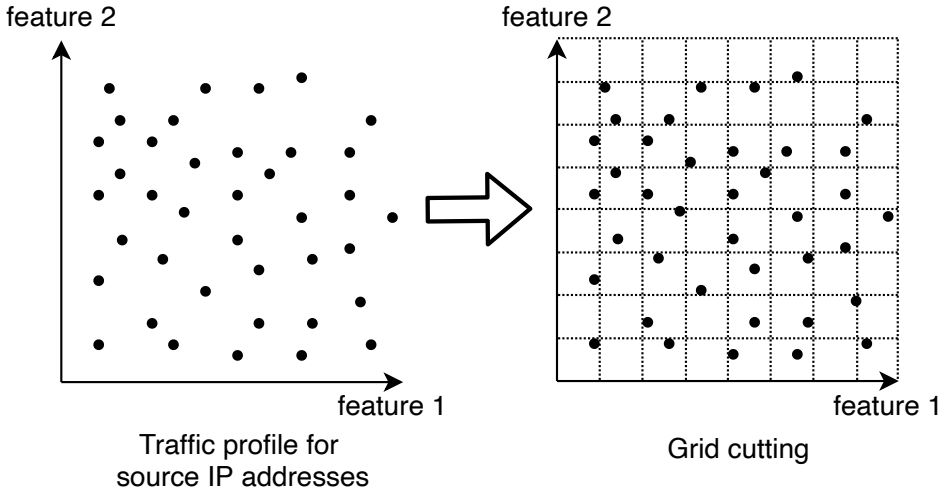
Phase two: DDoS classification

- Design philosophy: the traffic profile is currently in a malicious position, and we need to conduct access control on some of the sources, so that the traffic profile can return to a benign area.
  - First step: calculate the shortest path *p* of the current position to a benign area.





- We conduct the classification for malicious sources by building traffic profiles for each IP address.
- Then, mark IP as malicious in a particular order (according to *p*) until the overall traffic profile returns to a benign area.




```
malicious_IP = set()
eliminated_val = 0
D = sort(IP)  # Grid cutting
for i in D:
     Malicious_IP.add(i)
      eliminated_val += i.feature2
     if eliminated_val >= p:
          return malicious_IP
```

Adaptability

- Users do not need to retrain the proposed model to fit it into a different network environment. They can easily use some prior knowledge to refit the model:
  - If we have the **traffic measurement** information about the new environment, we can normalize the KNN searching space from the trained environment to the new environment according to the two networks' traffic distributions.
  - If the traffic monitoring system can obtain labeled traffic with the system running, we can efficiently conduct **online learning** on the proposed model.
  - In some circumstances, the user of this method may know some **incomplete threshold** values or rules in the new network environment. They can then build a decision tree based on the preliminary knowledge and merge it with the trained classifier, a tree-like data structure.

Thanks!