Comparison of Intrusion Detection Systems for Use in Low-Powered Devices

Pratyay Amrit (140953430)

Under the guidance of

Ms. Ipsita Upasana,
Assistant Professor
Department of I & CT
MIT, Manipal

Contents

Introduction

- Security in low powered devices
- Rise of IoT and WSN
- Intrusion Detection System (IDS)

Problem Definition

- Why IDS for low powered devices?
- Signature based IDS
- Anomaly based IDS
- Problems with low powered devices

Objectives

- To determine useful features in classifying network data.
- To find appropriate measures to score the different models.
- To study the causes of different models performing differently
- To open scope for future studies to improve the given score.

Scope

- Cyber Security service providers
- People working in IoT/WSN
- Further research

Methodology: Dataset

- UNSW-NB15 (over 2.5 million records)
- 9 types of attacks:
  Fuzzers
  Analysis
  Backdoor
  DoS
  Exploit
  Generic
  Reconnaissance
  Shell Code
  Worm

Methodology: Dataset

- 49 features divided into 6 categories:
- Flow Features(5), Basic Features(13), Content Features(8), Time Features(10), Additional Generated Features(11), Labeled Features(2)

Methodology: Pre-processing

- Import data (python pandas)
- Fill empty values
- Transform nominal to numeric
- Add feature names to Pandas DataFrame

Methodology: Feature Selection

- Use ExtraTreesClassifier
- Feature Importance Scores (gini impurity)

$$I_g(p) = 1 - \sum_{i=1}^{J} \left(p_i^2\right)$$

Methodology: K-Nearest Neighbors

- Popular classification algorithm.
- An object is classified as the class of the majority vote from the nearest k vectors in the feature space.

Methodology: Naive Bayes

- Popular classification algorithm.
- Assumption that features have no correlation.

$$p(C_k|X) = p(C_k)\prod_{i=1}^{n}(p(x_i|C_k))$$

Methodology: Decision Trees

- Generates tree-like model of decisions and their consequences.
- Information gain, gini impurity etc. are used to decide which feature to split at every level in the tree.

Methodology: Random Forests

- Ensemble Method
- Many small trees formed from random samples of the dataset.
- Decision on the basis of majority vote among individual trees.

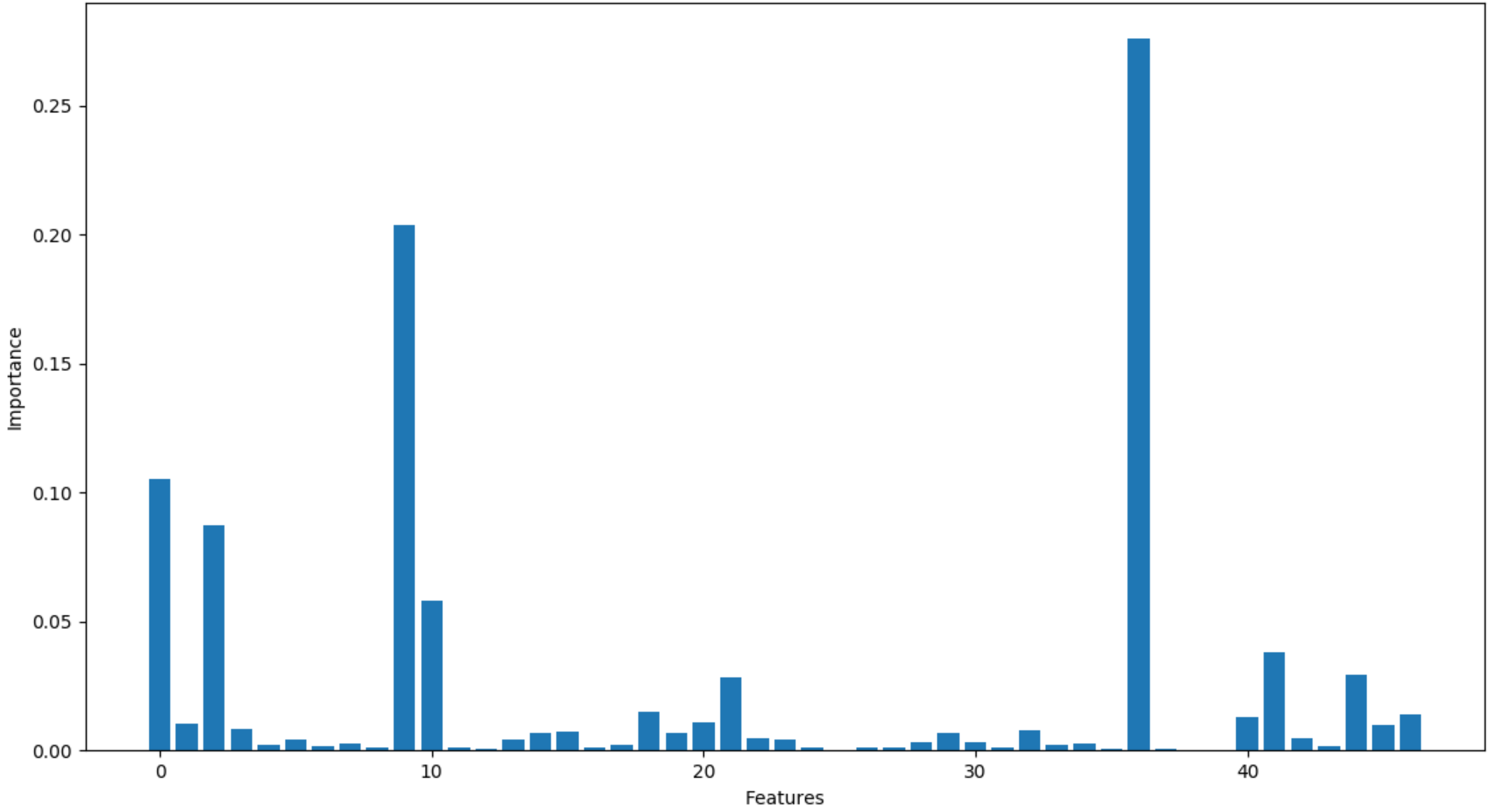
Methodology: Extra Trees

- Ensemble Method
- Similar to Random Forests.
- Split is decided using the entire dataset, instead of a random subset.

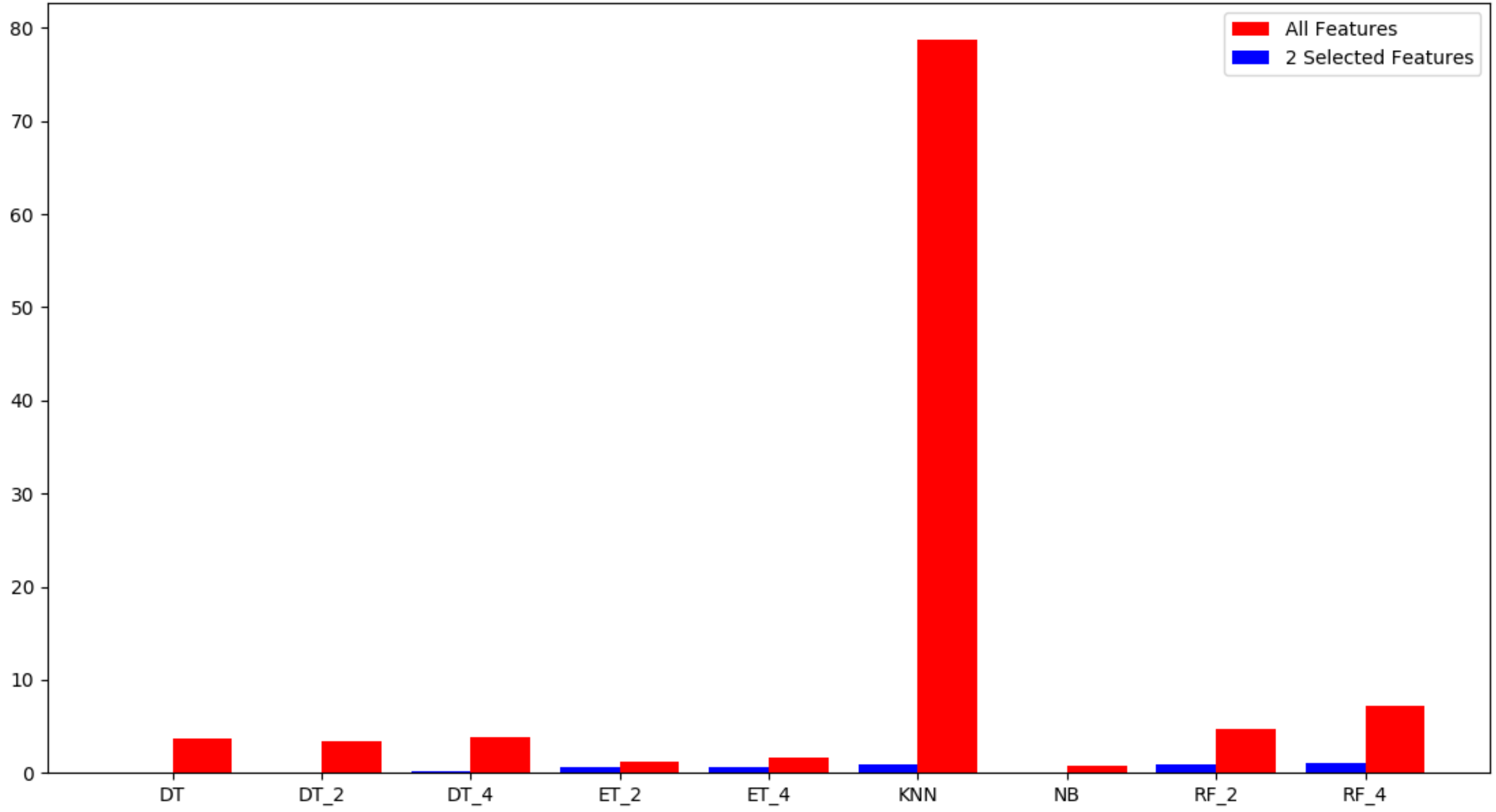
Methodology: Performance Parameters

- True Positive (TP): correctly classified attacks.
- True Negative (TN): correctly classified normal.
- False Positive (FP): incorrectly classified attacks.
- False Negative (FN): incorrectly classified normal.
- $accuracy = \frac{TP + TN}{TP + TN + FP + FN}$
- $TS = \frac{accuracy}{ttf}$ $\quad$ $PS = \frac{accuracy}{ttp}$

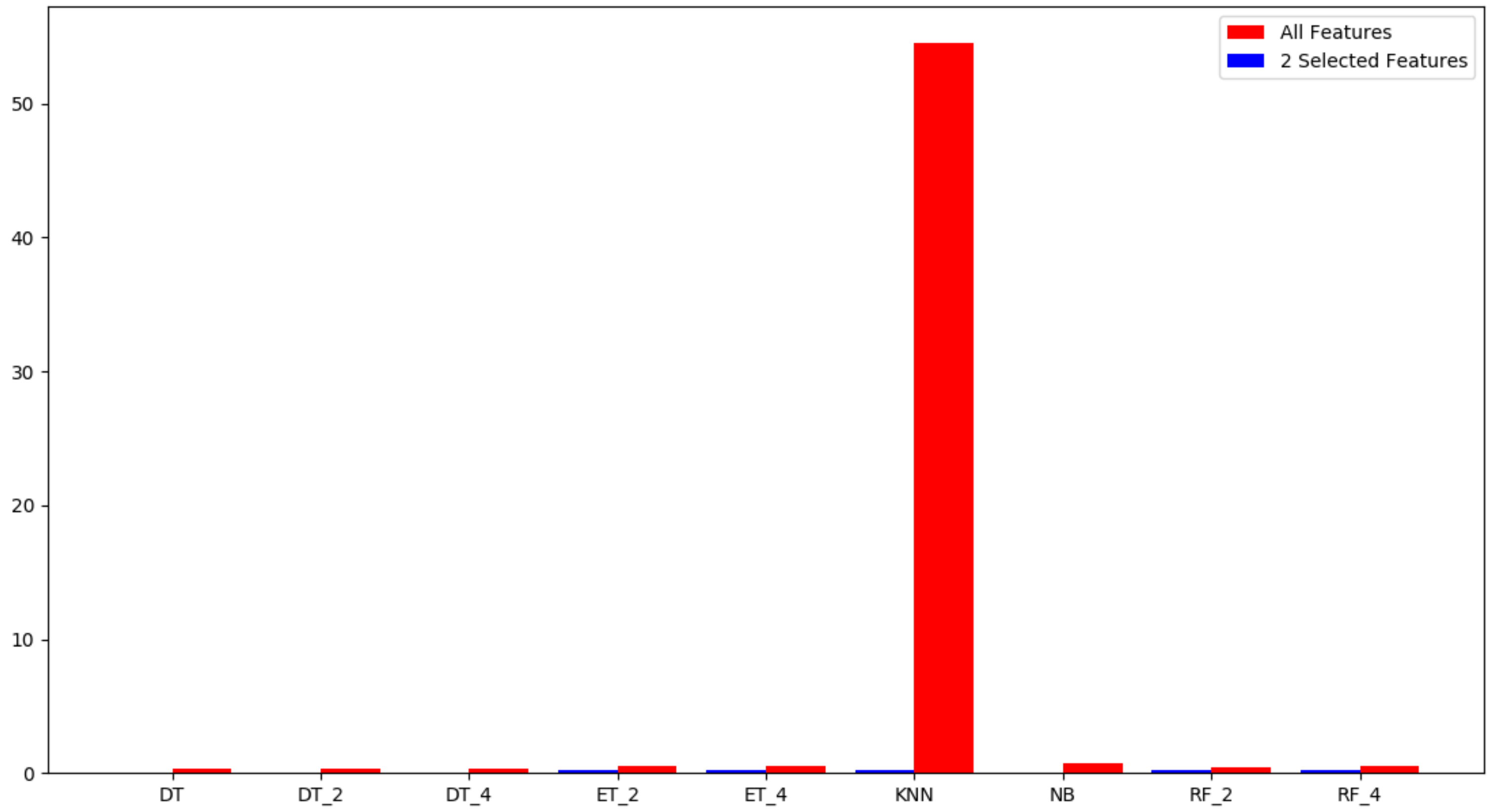
Results: Feature Selection



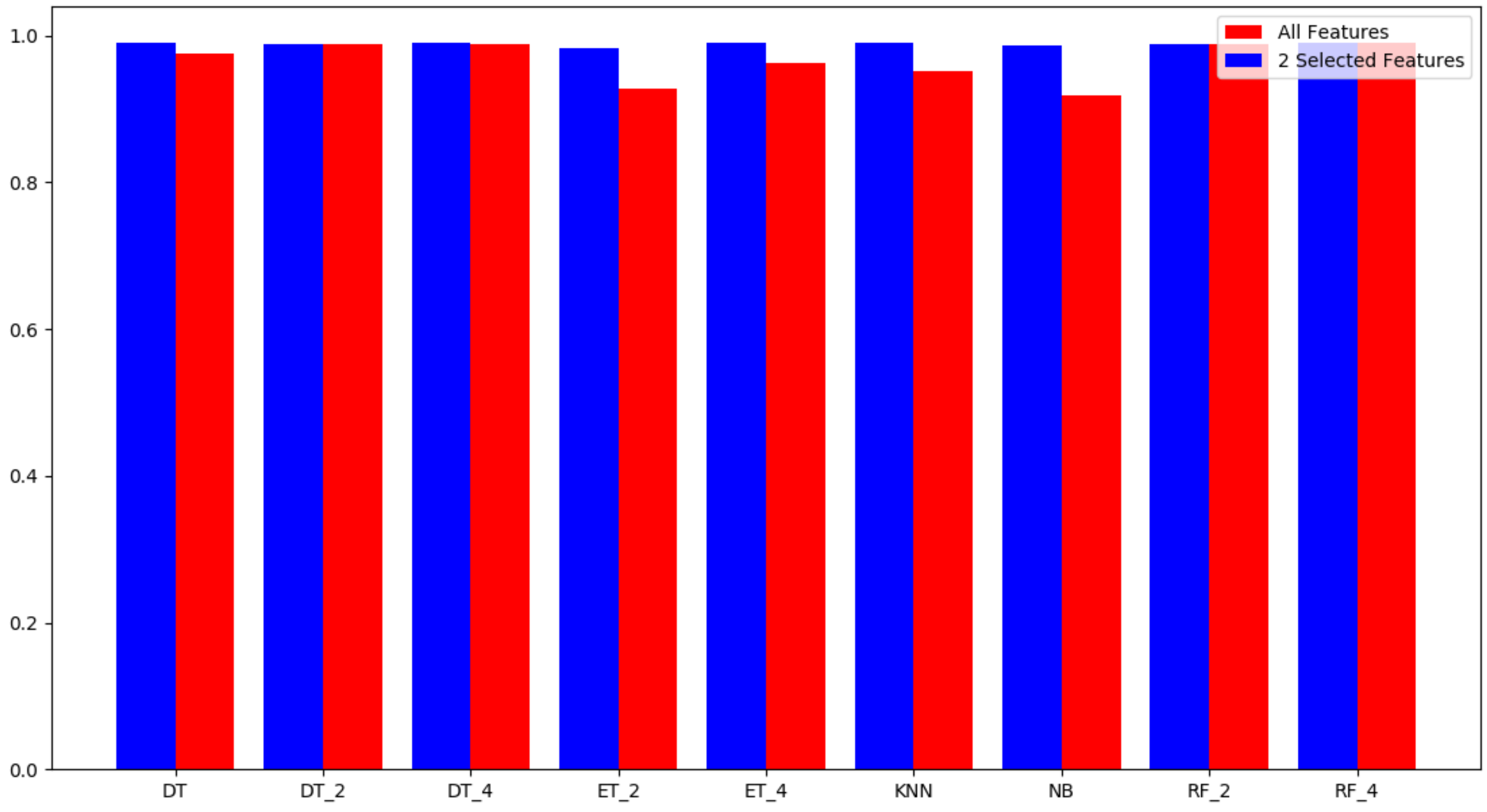
Results: Change in TTF (Table 4.1, 4.2)



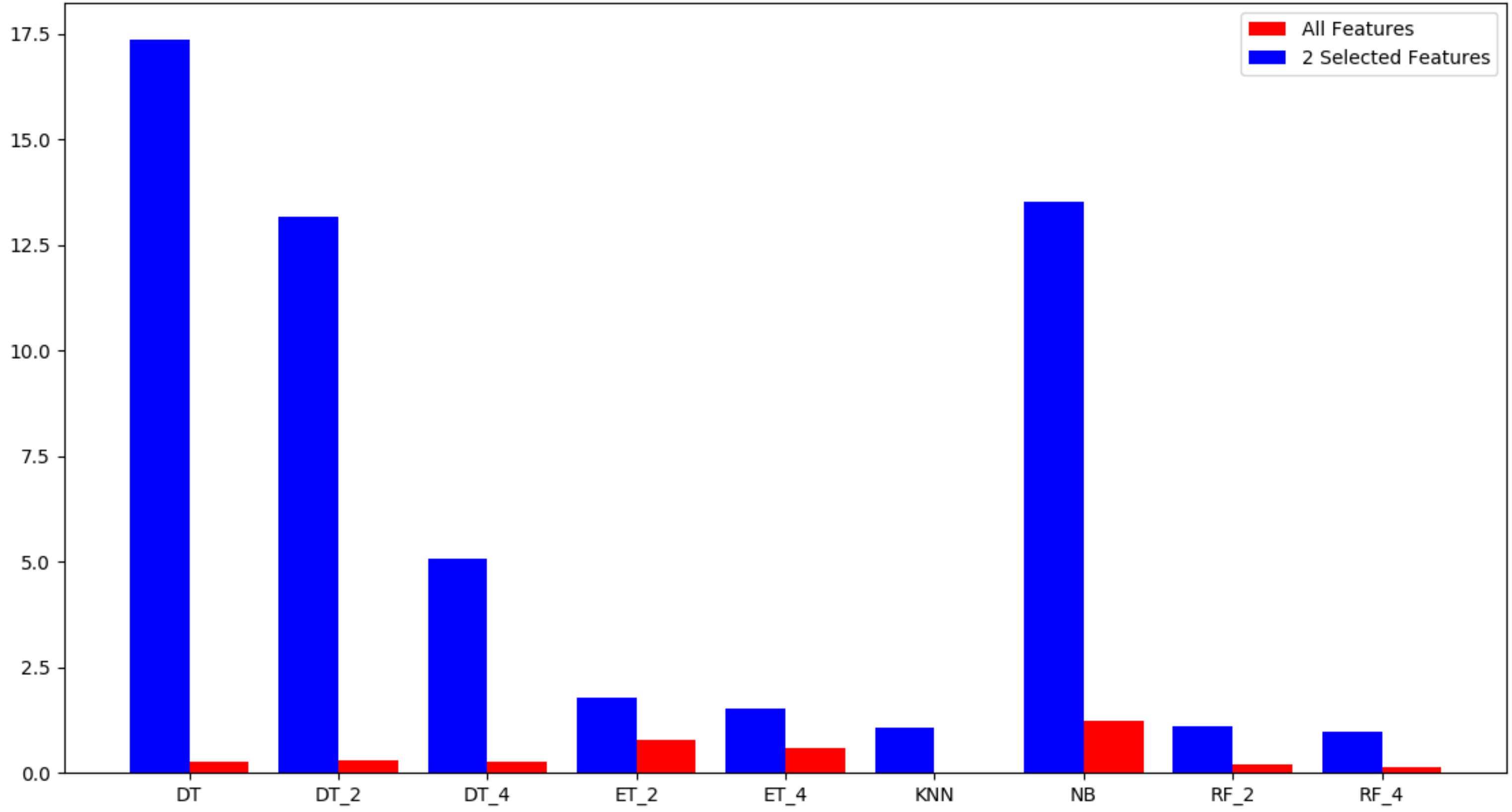
Results: Change in TTP (Table 4.1, 4.2)



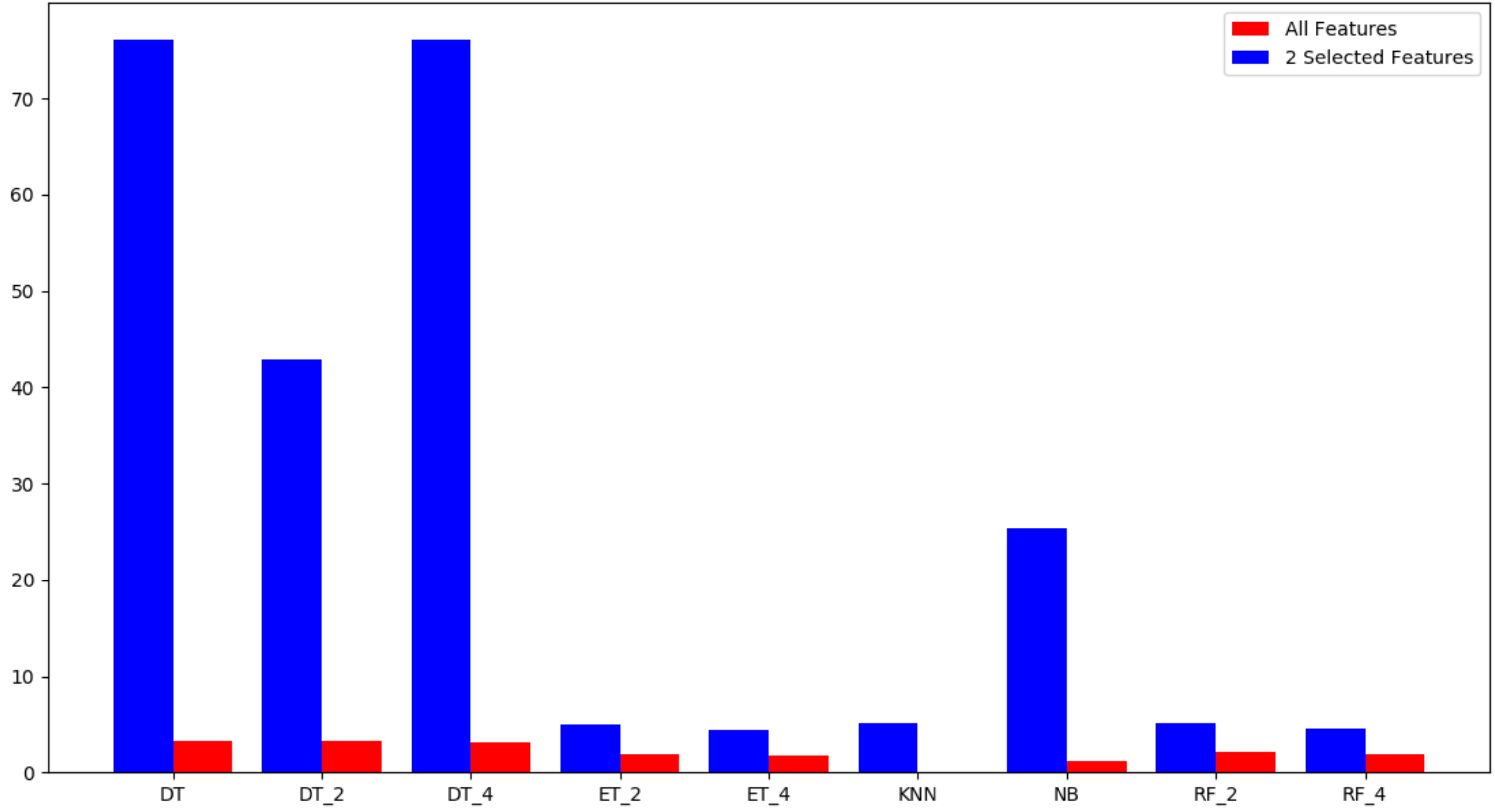
Results: Change in Accuracy (Table 4.1, 4.2)



Results: Change in TS (Table 4.3)



Results: Change in PS (Table 4.3)



Conclusion

- Importance of sttl, dttl and state for IDS.
- Decision Trees

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