HANOI UNIVERSITY OF SCIENCE AND TECHNOLOGY
SCHOOL OF INFORMATION AND COMMUNICATION TECHNOLOGY

APPLIED STATISTICS AND EXPERIMENTAL DESIGN

PROJECT: NETWORK ATTACKS DETECTION

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1 Introduction

Internet is not a new concept to everyone, it is a global system of interconnected computer networks, and everyone participates in data traffic between each other. However, for any web server, there is always a chance of getting attacked, whether by DDOS, Website Defacement, Directory Traversal, etc. To ensure secure, reliable, and qualitative network communication, we need a good way to analyze and supervise our traffic. Several models and methods have been proposed and implemented, and some attain desired efficiency and results to determine whether or not a connection is an attack or a normal one.

In this project, our group will try to build software to detect network intrusions protect a computer network from unauthorized users, including perhaps insiders. The intrusion detector learning task is to build a predictive model (i.e. a classifier) capable of distinguishing between "bad" connections, called intrusions or attacks, and "good" normal connections.[1]

Our report first will introduce the datasets we have chosen which is KDD Cup 1999 Dataset.[1] The following sections are exploratory data analysis (EDA) which we explored the data features, and patterns and then we tried different models for the attacks detection problem with suitable methods and evaluations. Finally, we will summarize what we have found out and some of the important points for this problem.

2 Exploratory Data Analysis (EDA)

Exploratory data analysis (EDA) is one of the most important steps before doing anything in every tabular dataset problem. As we used KDD Cup 1999 Dataset, EDA helps us gain insight into the dataset by visualizing charts and detecting any errors, and outliers as well as understanding different data patterns of many kinds of network attacks. In this section, we tried to depict what we have done and how we preprocessed the dataset.

2.1 Data Understanding & Visualization

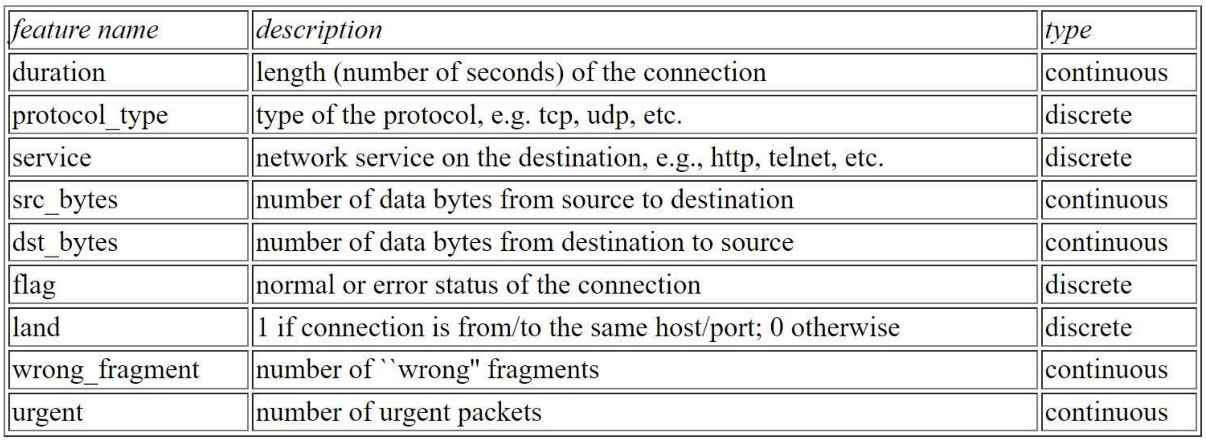
2.1.1 Datasets

Firstly, we will give a brief description of our dataset - KDD Cup 99.[1] Since 1999, it has been the most wildly used data set for the evaluation of anomaly detection (network attack detection) methods.[2] KDD training set contains nearly 4,900,000 instances (single connection between two computers) but we just selected 10 percent of the training set for training and evaluating our machine learning system. Every single connection is represented by 41 features and is labeled with exactly one specific type of attack. The simulated attacks are categorized into one of four categories:

- Denial of Service Attack (DoS)
- User to Root Attack (U2R)
- Remote to Local Attack (R2L)
- Probing Attack

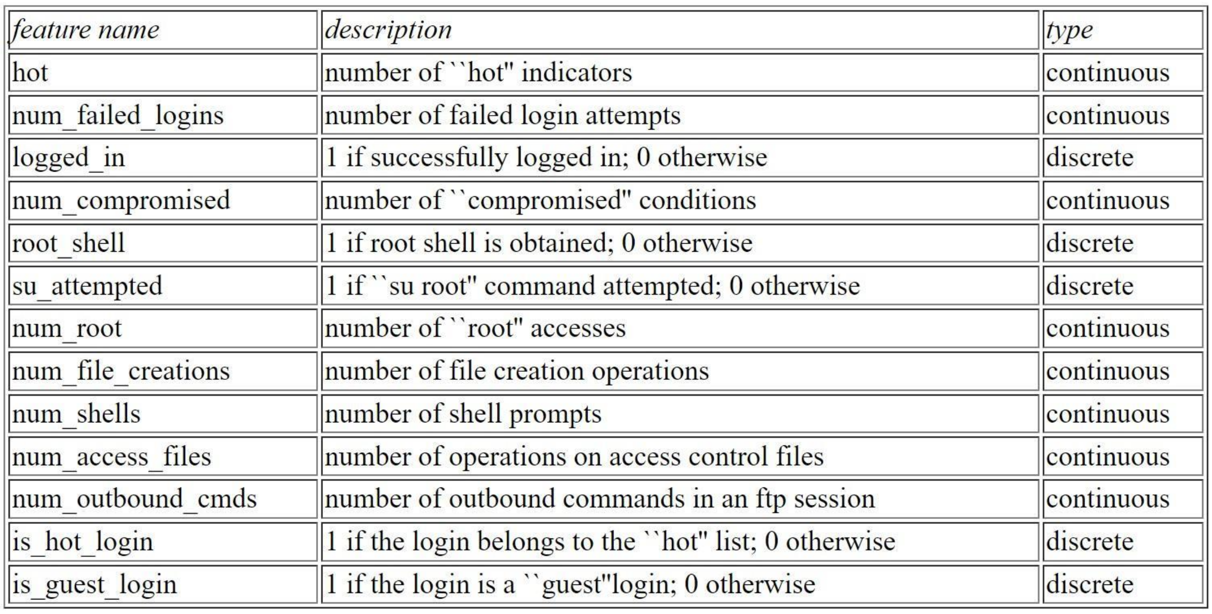
Besides the target variable, KDD Cup 99 features can be classified into three groups (two derived feature categories):

- **Basic features**: This category contains all features which can be extracted directly from the TCP/IP connections.
- **Content features**: This category includes all features which can be inferred by the domain knowledge of experts which helps us to classify better
- **Traffic features**: This category contains all features which could be calculated by using a two second time window (before the current connection)



feature name	*description*	*type*
duration	length (number of seconds) of the connection	continuous
protocol_type	type of the protocol, e.g. tcp, udp, etc.	discrete
service	network service on the destination, e.g., http, telnet, etc.	discrete
src_bytes	number of data bytes from source to destination	continuous
dst_bytes	number of data bytes from destination to source	continuous
flag	normal or error status of the connection	discrete
land	1 if connection is from/to the same host/port; 0 otherwise	discrete
wrong_fragment	number of ``wrong'' fragments	continuous
urgent	number of urgent packets	continuous

Basic features of individual TCP connections



feature name	*description*	*type*
hot	number of ``hot'' indicators	continuous
num_failed_logins	number of failed login attempts	continuous
logged_in	1 if successfully logged in; 0 otherwise	discrete
num_compromised	number of ``compromised'' conditions	continuous
root_shell	1 if root shell is obtained; 0 otherwise	discrete
su_attempted	1 if ``su root'' command attempted; 0 otherwise	discrete
num_root	number of ``root'' accesses	continuous
num_file_creations	number of file creation operations	continuous
num_shells	number of shell prompts	continuous
num_access_files	number of operations on access control files	continuous
num_outbound_cmds	number of outbound commands in an ftp session	continuous
is_hot_login	1 if the login belongs to the ``hot'' list; 0 otherwise	discrete
is_guest_login	1 if the login is a ``guest''login; 0 otherwise	discrete

Content features within a connection suggested by domain knowledge

2.1.2 Data Exploration

a. Univariate Analysis

Firstly, we will plot all the histograms of all numeric attributes in order to give us a brief information about the distribution of some numeric features

Overall, numeric features in KDD Cup 99 are severely suffered from skewness, almost features have one dominant value such as (duration, src bytes,dst bytes). Therefore, we thought that maybe some outliers of those attributes would indicate which connections are bad.

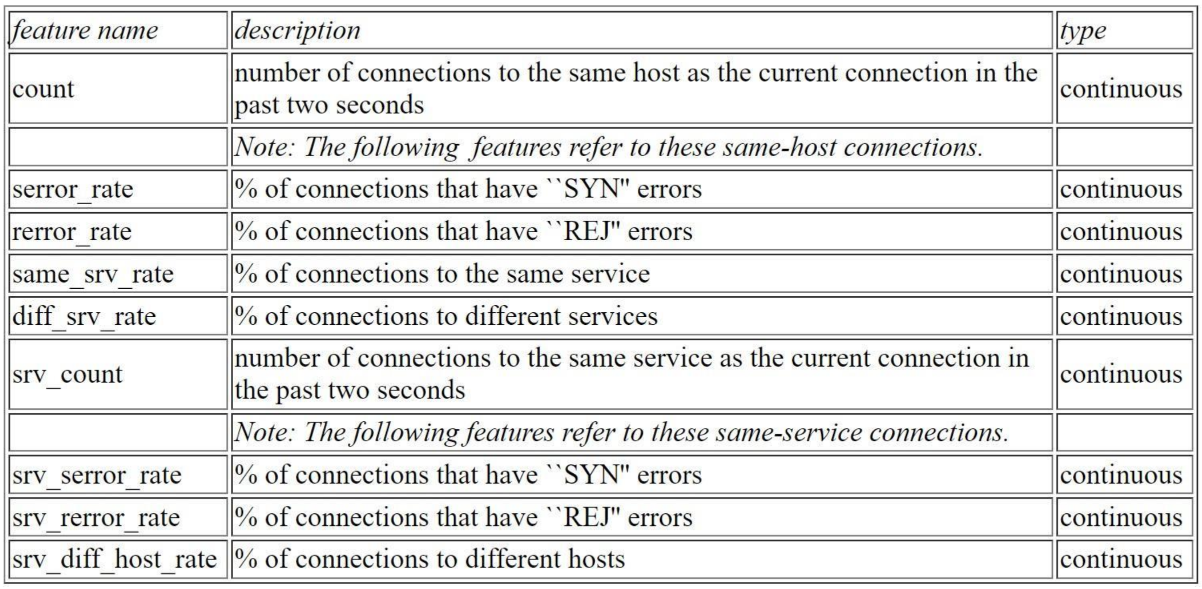
After that, we will also plot all histograms of all categorical attributes including target, flag, service, and protocol _type

In general, all connections fall into three dominant types (smurf, neptune, and normal) as well as ecr _i, private, and http are the most popular service features in the dataset.

Finally, we will also take into account the distribution of our target label which is 'Attack Type' . As we can see, the almost connection is labeled as 'dos' which accounts for nearly 80%. Furthermore, 19.6% belong to normal connection and another small percentage falls into other attack types.

b. Multivariate Analysis

In this part, we will analyze the relationship between some independent features with dependent



feature name	*description*	*type*
count	number of connections to the same host as the current connection in the past two seconds	continuous
	Note: The following features refer to these same-host connections.	
serror_rate	% of connections that have ``SYN'' errors	continuous
rerror_rate	% of connections that have ``REJ'' errors	continuous
same_srv_rate	% of connections to the same service	continuous
diff_srv_rate	% of connections to different services	continuous
srv_count	number of connections to the same service as the current connection in the past two seconds	continuous
	Note: The following features refer to these same-service connections.	
srv_serror_rate	% of connections that have ``SYN'' errors	continuous
srv_rerror_rate	% of connections that have ``REJ'' errors	continuous
srv_diff_host_rate	% of connections to different hosts	continuous

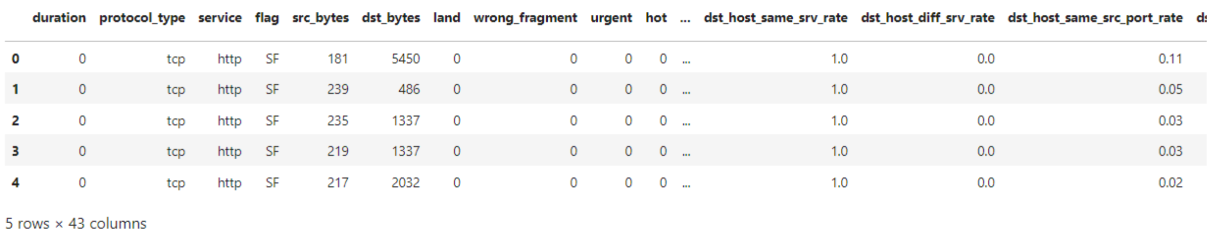
features as well as the correlation between each independent features which would help us tremendously at data preparation stage.

Our first step is finding the relationship between some independent features (protocol type, is guest login) towards the target attribute ('Attack Type'). For the influence of protocol type, udp protocol type will tend to have normal connections whereas the connection with tcmp will tend to be dos. So we decided to keep this feature rather than drop it.

Next, we plot the correlation between independent variables. In general, there are many high correlation between some pairs of variables such as (num root, num compromised), (srv serror rate, serror rate), (dst host serror rate, serror rate), etc. which will help us to remove some redundant variables in the dataset.

2.1.3 Simple EDA

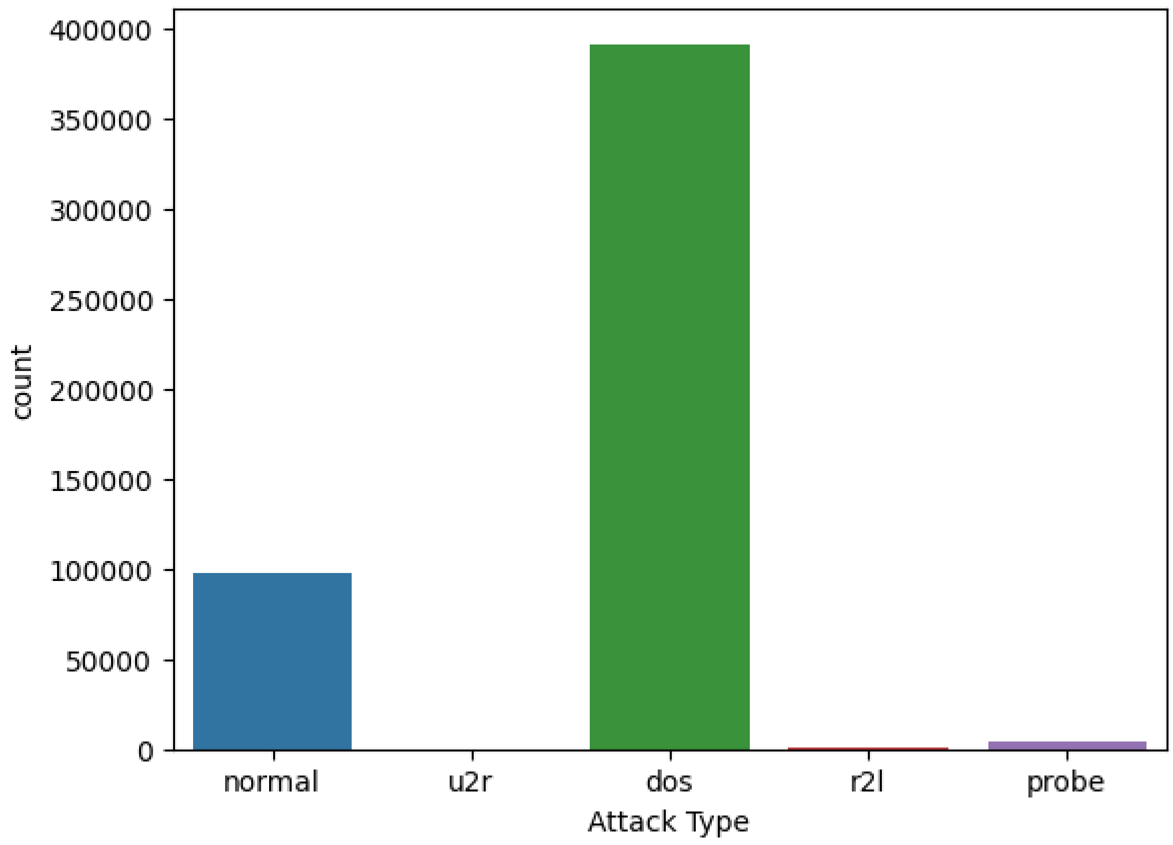
Our dataset has 43 features



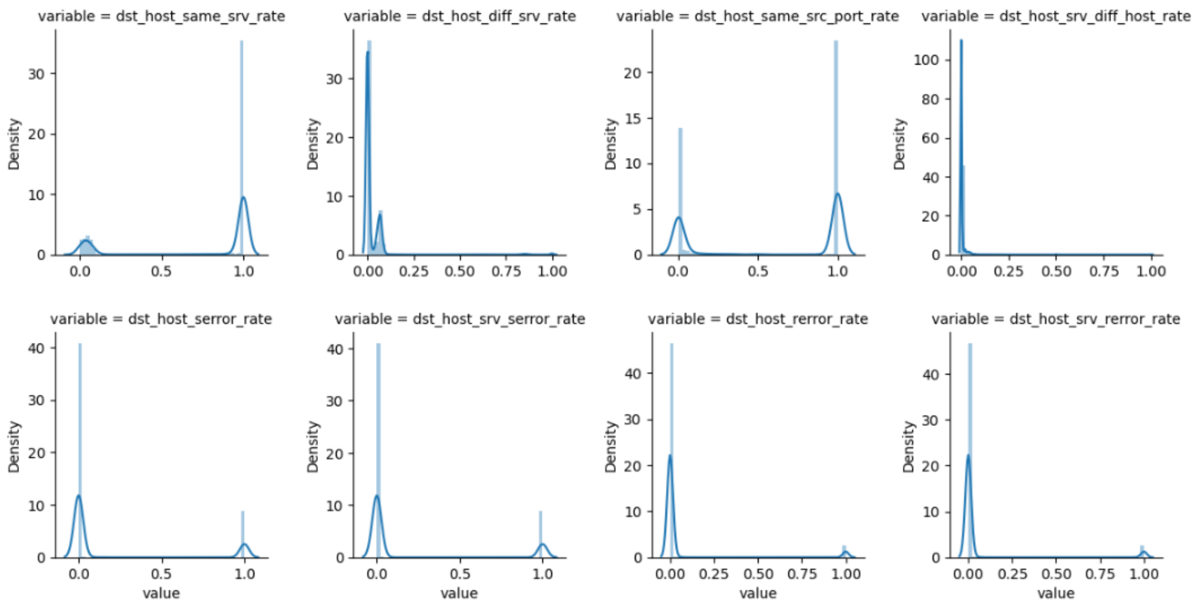
	duration	protocol_type	service	flag	src_bytes	dst_bytes	land	wrong_fragment	urgent	hot	...	dst_host_same_srv_rate	dst_host_diff_srv_rate	dst_host_same_src_port_rate	d
0	0	tcp	http	SF	181	5450	0	0	0	0	...	1.0	0.0	0.11	
1	0	tcp	http	SF	239	486	0	0	0	0	...	1.0	0.0	0.05	
2	0	tcp	http	SF	235	1337	0	0	0	0	...	1.0	0.0	0.03	
3	0	tcp	http	SF	219	1337	0	0	0	0	...	1.0	0.0	0.03	
4	0	tcp	http	SF	217	2032	0	0	0	0	...	1.0	0.0	0.02	

5 rows × 43 columns

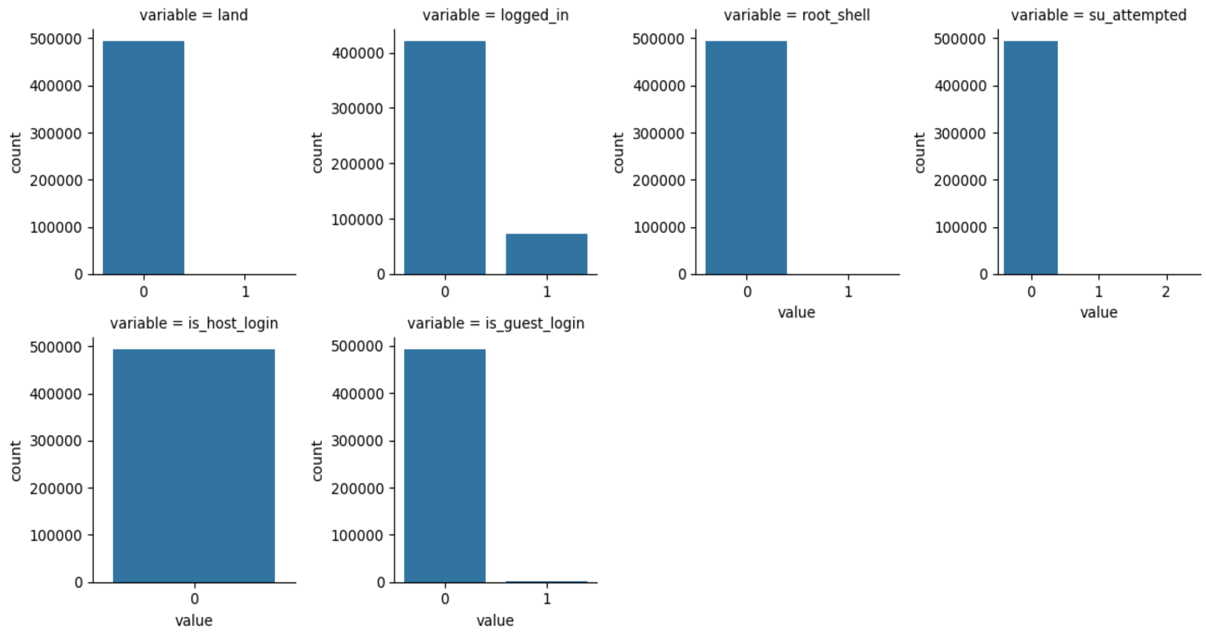
a. Count Histogram of Attack Type(output)



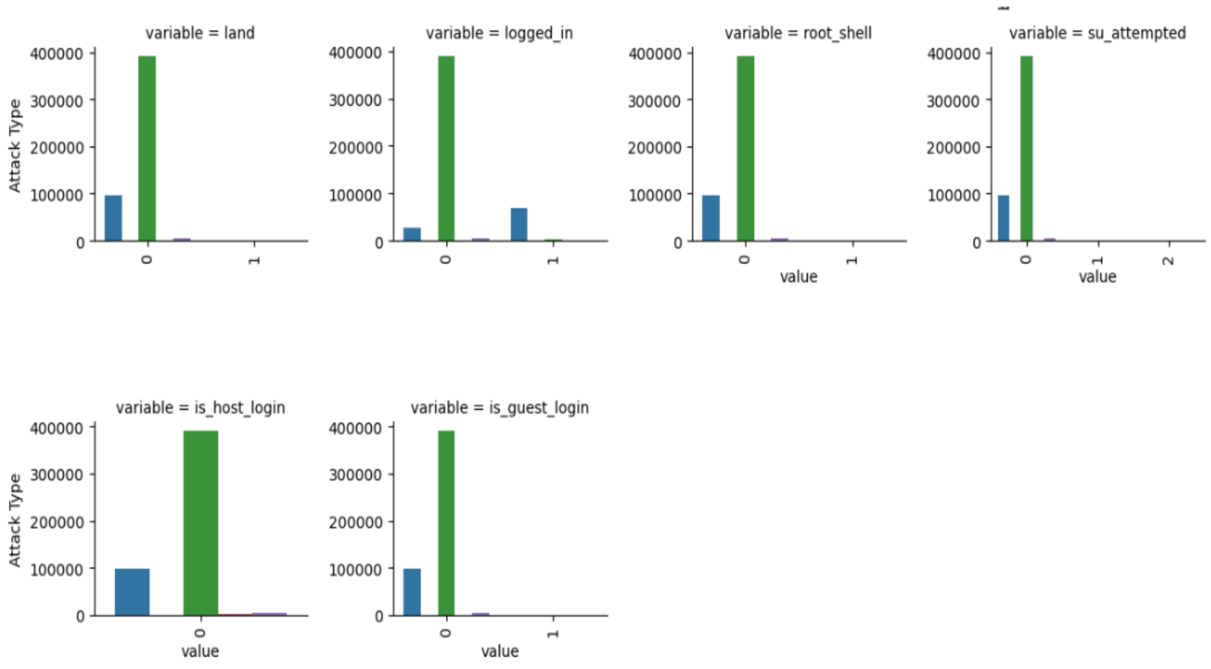
b. Distribution of Some Continuous Variables



c. Count Histogram of Discrete Variables



d. Count Histogram of Some Categorical Variables



2.2 Data Preparation

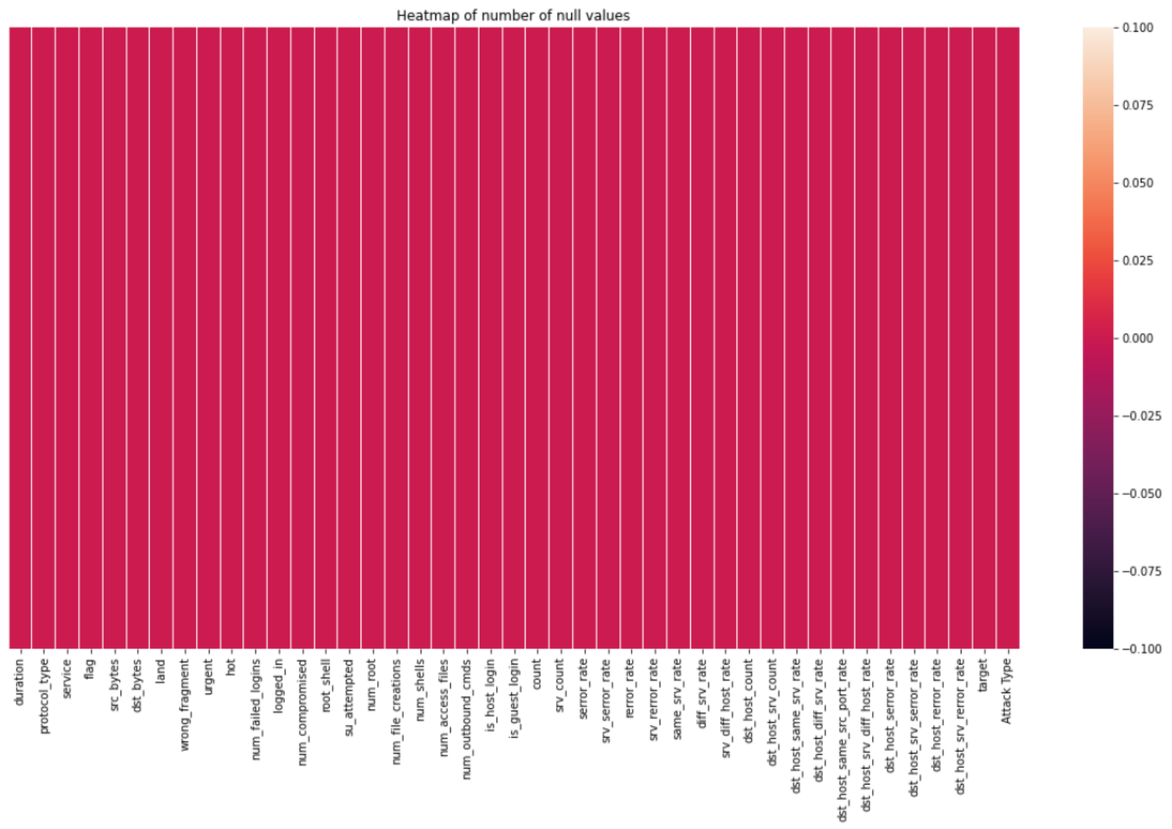
Data preparation is a pre-processing step that involves cleansing, transforming, and consolidating data.[3] In this part, we will illustrate how we preprocessed our dataset based on the previous section (EDA).

Firstly, from the count histogram of attack type, you can see that the number of classes is very different, most of them belong to 2 classes, dos and normal, the remaining 3 classes account for a very small and insignificant number so we combine these 3 classes into 1 new class named "other" to increase the performance of the model.

2.2.1 Data Cleaning

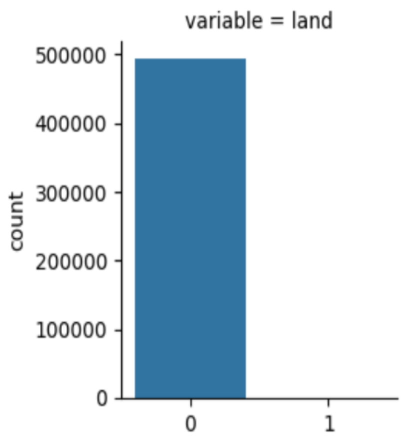
a. Missing Value

In the first step, we would like to check whether there is a missing value in each feature in the dataset. Therefore, we depicted the heatmap of null values for each attribute in . As we can see, there are no null values for all attributes so we decided to not drop a feature or delete any instances yet.



b. Redundant Variables

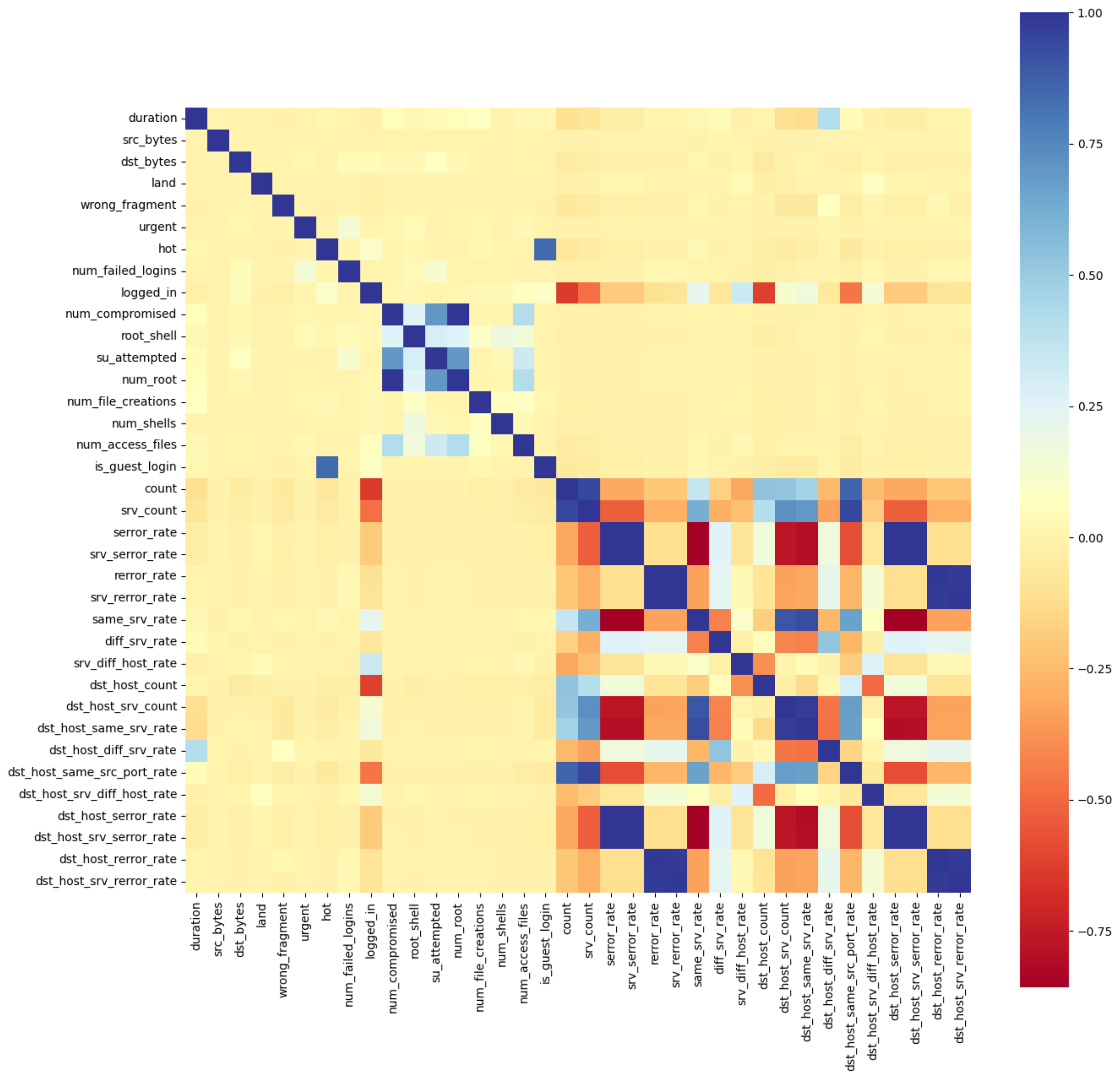
In this step, we would like to remove redundant variables where they have only one unique value such as (land) and some variables which have a high correlation value with other variables such as (num root, srv serror rate, etc.). We found that there are 8 features that have high correlation with the others.



Count Histogram of Land Feature

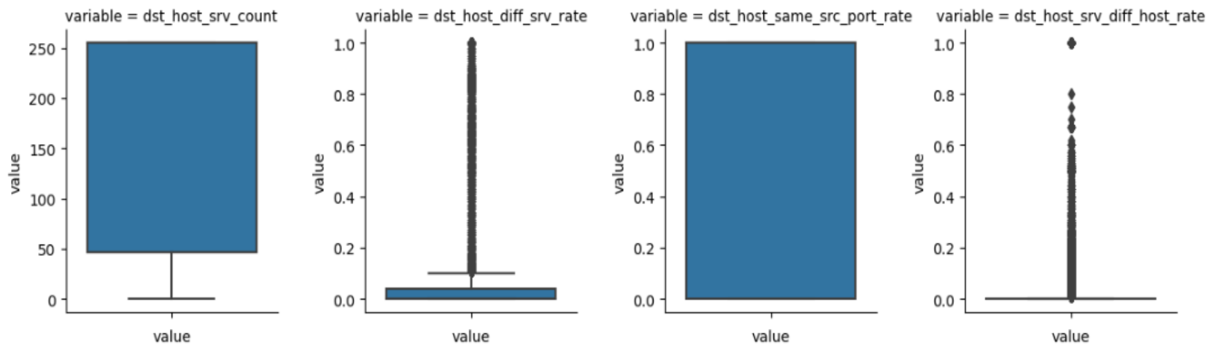
We also remove “target” feature, which have the same meaning as “Attack Type”

After doing these steps, our training set has 33 features (less than 10 features than the raw dataset)



Correlation of Continuous Variables

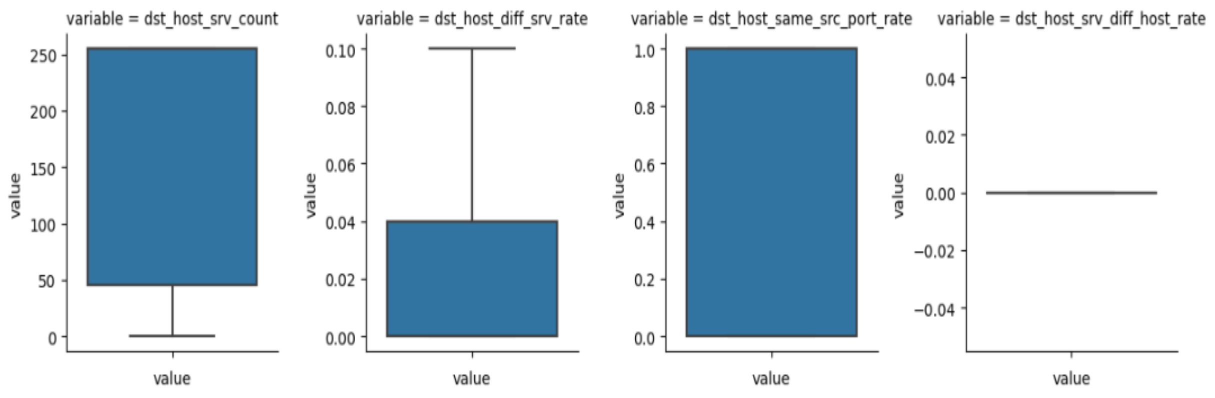
c. Outliers



Outliers before treating

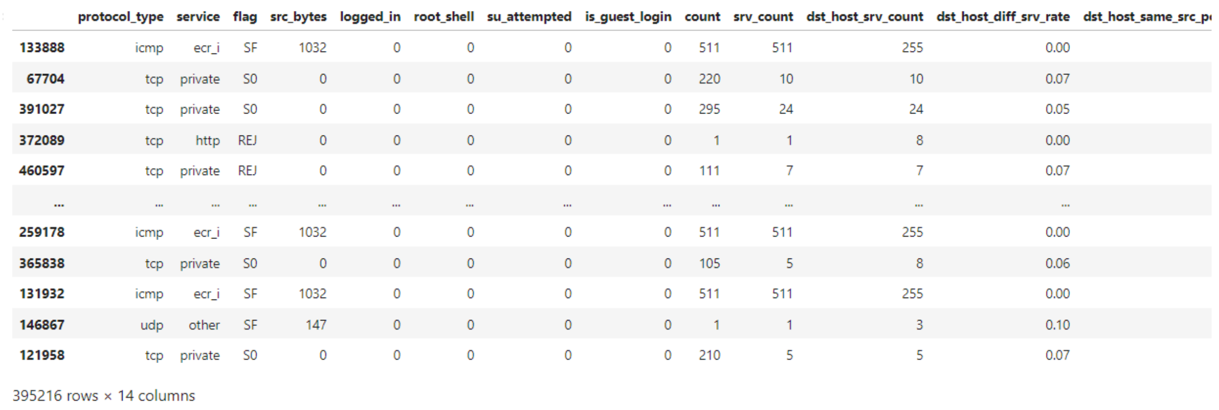
Outliers are those data points that are significantly different from the rest of the dataset. They are often abnormal observations that skew the data distribution, and arise due to inconsistent data entry, or erroneous observations.In this problem, Outliers are abnormal observations,scale is deviated from most of the other values in that field,which skew the data distribution and often reduce the performance of the model,so we need to treating outliers before put into model.

According to statistical theory, almost 99% of the value of a random variable is between Q1-1.5IQR(lower) and Q3+1.5IQR(upper),points outside this range are outliers and we need to deal with these points. I selected clips of outlier points about lower and upper.



Outliers after treating

After treating the outliers, we have removed 19 features that only have one value. Now our dataset has only 14 attributes



	protocol_type	service	flag	src_bytes	logged_in	root_shell	su_attempted	is_guest_login	count	srv_count	dst_host_srv_count	dst_host_diff_srv_rate	dst_host_same_src_p
133888	icmp	ecr_i	SF	1032	0	0	0	0	511	511	255	0.00	
67704	tcp	private	S0	0	0	0	0	0	220	10	10	0.07	
391027	tcp	private	S0	0	0	0	0	0	295	24	24	0.05	
372089	tcp	http	REJ	0	0	0	0	0	1	1	8	0.00	
460597	tcp	private	REJ	0	0	0	0	0	111	7	7	0.07	
...	...	...	...	...	...	...	...	...	...	...	...	...	
259178	icmp	ecr_i	SF	1032	0	0	0	0	511	511	255	0.00	
365838	tcp	private	S0	0	0	0	0	0	105	5	8	0.06	
131932	icmp	ecr_i	SF	1032	0	0	0	0	511	511	255	0.00	
146867	udp	other	SF	147	0	0	0	0	1	1	3	0.10	
121958	tcp	private	S0	0	0	0	0	0	210	5	5	0.07	

395216 rows × 14 columns

2.2.2 Variable Transformations

a. Encoder

The categorical variables in this problem are all nominal so we cannot use encode operations such as label encode or ordinal encode, not only that, the number of values in each categorical variables is also quite large, so we cannot use one-hot encode or encoders based on one-hot encode. Here we choose JamesSteinEncoder as an encoder whose base is target encoder. To do that we have to create a feature target

in binary form. is "label_transform'' Obviously we are more interested in whether the network is attacked than what type of attack it is, so we encode ''normal'' = 1 and other type of attack = 0. We then apply JamesSteinEncoder's theory directly on categorical variables and feature ''label_transform''
For feature value i, James-Stein estimator returns a weighted average of:

1.The mean target value for the observed feature value i.

2.The mean target value (regardless of the feature value).

This can be written as:

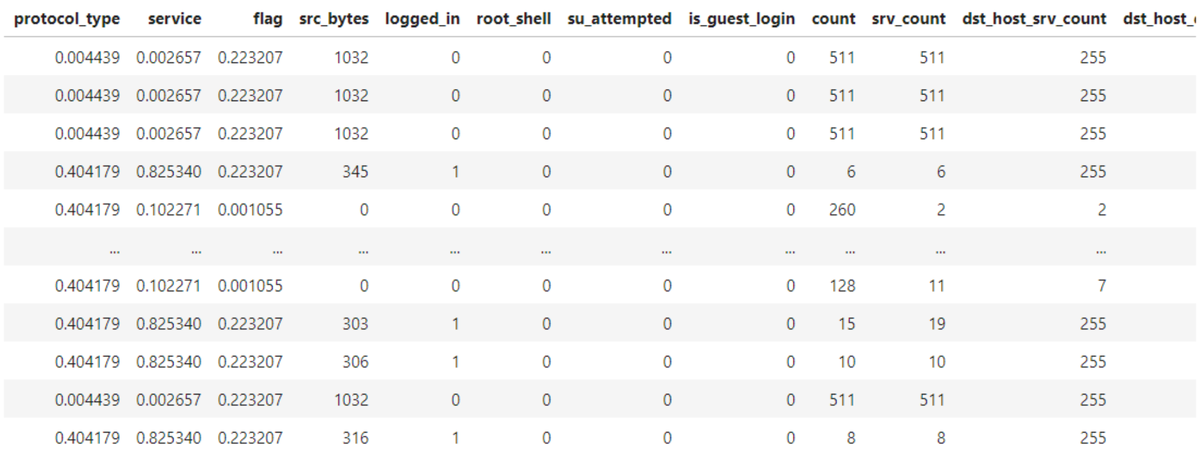
JS_i = (1-B)*mean(y_i) + B*mean(y)

The question is, what should be the weight B? If we put too much weight on the conditional mean value, we will overfit. If we put too much weight on the global mean, we will underfit. The canonical solution in machine learning is to perform cross-validation. However, Charles Stein came with a closed-form solution to the problem. The intuition is: If the estimate of mean(y_i) is unreliable (y_i has high variance), we should put more weight on mean(y). Stein put it into an equation as:

B = var(y_i) / (var(y_i)+var(y))

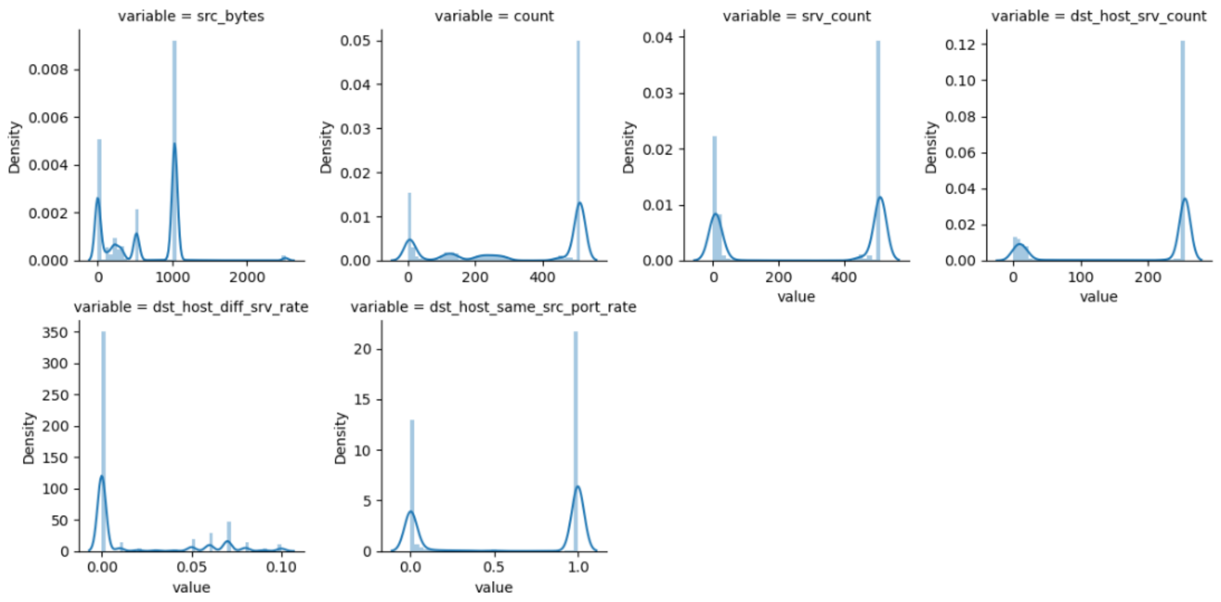
b. Normalization and Scaling

Finally, before putting data into the model for training, we need to normalize and scale the data



protocol_type	service	flag	src_bytes	logged_in	root_shell	su_attempted	is_guest_login	count	srv_count	dst_host_srv_count	dst_host_
0.004439	0.002657	0.223207	1032	0	0	0	0	511	511	255	
0.004439	0.002657	0.223207	1032	0	0	0	0	511	511	255	
0.004439	0.002657	0.223207	1032	0	0	0	0	511	511	255	
0.404179	0.825340	0.223207	345	1	0	0	0	6	6	255	
0.404179	0.102271	0.001055	0	0	0	0	0	260	2	2	
...	...	...	...	...	...	...	...	...	...	...	
0.404179	0.102271	0.001055	0	0	0	0	0	128	11	7	
0.404179	0.825340	0.223207	303	1	0	0	0	15	19	255	
0.404179	0.825340	0.223207	306	1	0	0	0	10	10	255	
0.004439	0.002657	0.223207	1032	0	0	0	0	511	511	255	
0.404179	0.825340	0.223207	316	1	0	0	0	8	8	255	

Data before scaling



Distribution Of Continuous Variables

It can be seen that the data has fields with quite different scales, for example, the protocol_type,service,flag fields have values in those fields ranging from 0->1 while the src_bytes or srv_counts fields have values ranging from the hundred to thousand, not only that the distribution of continuous variables don't fit with 1 normal distribution is skewed or can be seen by mixing 2 or more different normal distributions. From the above 2 reasons, we use Min-Max scaler to normalize data

3 Modeling

3.1 Probabilistic models

In this section, we want to mention probabilistic models first. This is because the majority of this project was about statistical analysis therefore we were more likely to apply models that involve uncertainty before the others.

3.1.1 Gaussian Naive Bayes

Before diving into Gaussian Naive Bayes, we will mention the overview of Naive Bayes methods. These are a set of supervised learning algorithms based on applying Bayes' theorem with the "naive" assumption of conditional independence between every pair of features given the value of the class variable. Bayes' theorem states the following relationship, given class variable *y* and dependent feature vector x_1 through x_n, :

$$P(y \mid x_1, \ldots, x_n) = \frac{P(y) P(x_1, \ldots, x_n \mid y)}{P(x_1, \ldots, x_n)}$$

Using the naive conditional independence assumption that:

$$P(x_i|y, x_1, \ldots, x_{i-1}, x_{i+1}, \ldots, x_n) = P(x_i|y)$$

for all *i*, this relationship is simplified to:

$$P(y \mid x_1, \ldots, x_n) = \frac{P(y) \prod_{i=1}^{n} P(x_i \mid y)}{P(x_1, \ldots, x_n)}$$

When working with continuous data, an assumption often taken is that the continuous values associated with each class are distributed according to a Normal Distribution (or Gaussian Distribution). The likelihood of the features is assumed to be Gaussian:

$$P(x_i \mid y) = \frac{1}{\sqrt{2\pi\sigma_y^2}} \exp\left(-\frac{(x_i - \mu_y)^2}{2\sigma_y^2}\right)$$

An approach to creating a simple model is to assume that the data is described by a Gaussian distribution with no co-variance (independent dimensions) between dimensions. This model can be fit by simply finding the mean and standard deviation of the points within each label, which is all that is needed to define such a distribution.

3.1.2 Multinomial Naive Bayes

While Gaussian Naive Bayes supports continuous-valued features, the Multinomial Naive Bayes classifier is suitable for classification with discrete features. This algorithm is one of the two classic naive Bayes variants used in text classification. The multinomial distribution normally requires integer feature counts. The distribution is parametrized by vectors $\theta_y = (\theta_{y1},...,\theta_{yn})$ for each class y, where n is the number of features and θ_{yi} is the probability $P(x_i|y)$ of feature i appearing in a sample belonging to class y.
The parameters θ_y is estimated by a smoothed version of maximum likelihood:

$$\hat{\theta}_{yi} = \frac{N_{yi} + \alpha}{N_y + \alpha n}$$

where N_{yi} = P $_{x\in T}\, x_i$ is the number of times feature i appears in a sample of class y in the training set T, and $N_y = \sum_{i=1}^{n} N_{yi}$ is the total count of all features for class y.
The smoothing priors $\alpha \geq 0$ account for features not present in the learning samples and prevents zero probabilities in further computations. Setting $\alpha = 1$ is called Laplace smoothing, while $\alpha < 1$ is called Lidstone Smoothing.

3.1.3 Gaussian Mixture Model

A Gaussian mixture model is a probabilistic model that assumes all the data points are generated from a mixture of a finite number of Gaussian distributions with unknown parameters. One can think of mixture models as generalizing k-means clustering to incorporate information about the covariance structure of the data as well as the centers of the latent Gaussian Models.

A Gaussian mixture model is parameterized by two types of values, the mixture **component weights** and the component **means** and **variances/covariances**. For a Gaussian mixture model with K component, the k^{th} component has a mean of μ_k and variance of σ_k.

If the number of components K is known, **expectation maximization** is the technique most commonly used to estimate the mixture model's parameters. In Frequentist Probability theory, models are typically learned by using maximum likelihood estimation techniques, which seek to maximize the probability, or likelihood, of the observed data given the model parameters. Unfortunately, finding the maximum likelihood solution for mixture models by differentiating the log likelihood and solving for 0 is usually analytically impossible.

1. The first step, known as the expectation step or E step, consists of calculating the expectation of the component assignments C_k for each data point $x_i \in X$ given the model parameters ϕ_k,μ_k , and σ_k.
2. The second step is known as the maximization step or M step, which consists of maximizing the expectations calculated in the E step with respect to the model parameters. This step consists of updating the values ϕ_k,μ_k , and σ_k.

When the number of components K is not known a priori, it is typical to guess the number of components and fit that model to the data using the EM algorithm. This is done for many different values of K. Usually, the model with the best trade-off between fit and number of components is kept.

Since the number of classes remaining after we process is 3, the n_components parameter selected in this model is 3.

3.2 Other Machine Learning Models

We also want to apply some other Machine Learning Models for comparing and improving results.

3.2.1 Logistic Regression

Logistic Regression is an example of a classification algorithm which is used to find a relationship between features and the probability of a particular outcome. ”Logistic” is taken from the Logit Function that is used in this method of classification. The term ”Regression” comes from its underlying technique which is quite the same as Linear regression. However, unlike regular regression, the outcome calculates the predicted probability of mutually exclusive events occurring based on multiple external factors. Now, we will focus more on the Logit Function.

We have the linear regression equation:

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_n X_n$$

Here, y is dependent variable and $X_1, X_2, ... X_n$ are explanatory variables. The sigmoid function can be written as:

$$P = \frac{1}{1 + e^{-y}}$$

The sigmoid function gives an S-shaped curve. It always gives a value of probability ranging from $0 < P < 1$. The function can take any real-valued number and map it into a value between 0 and 1. If we apply the sigmoid equation to the linear regression equation, we have the equation for Logistic Regression:

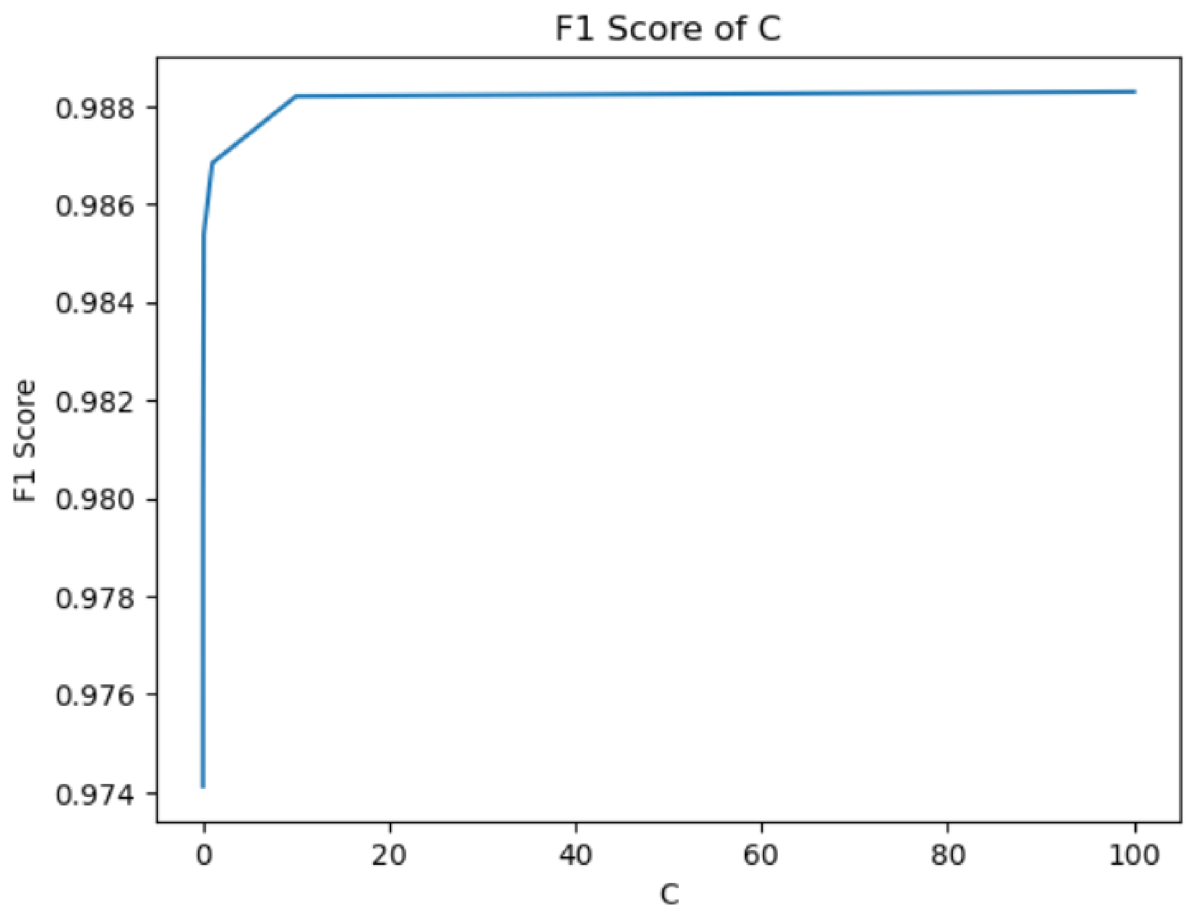
$$P = \frac{e^{(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_n X_n)}}{1 + e^{(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_n X_n)}}$$

Logistic regression can be expressed as:

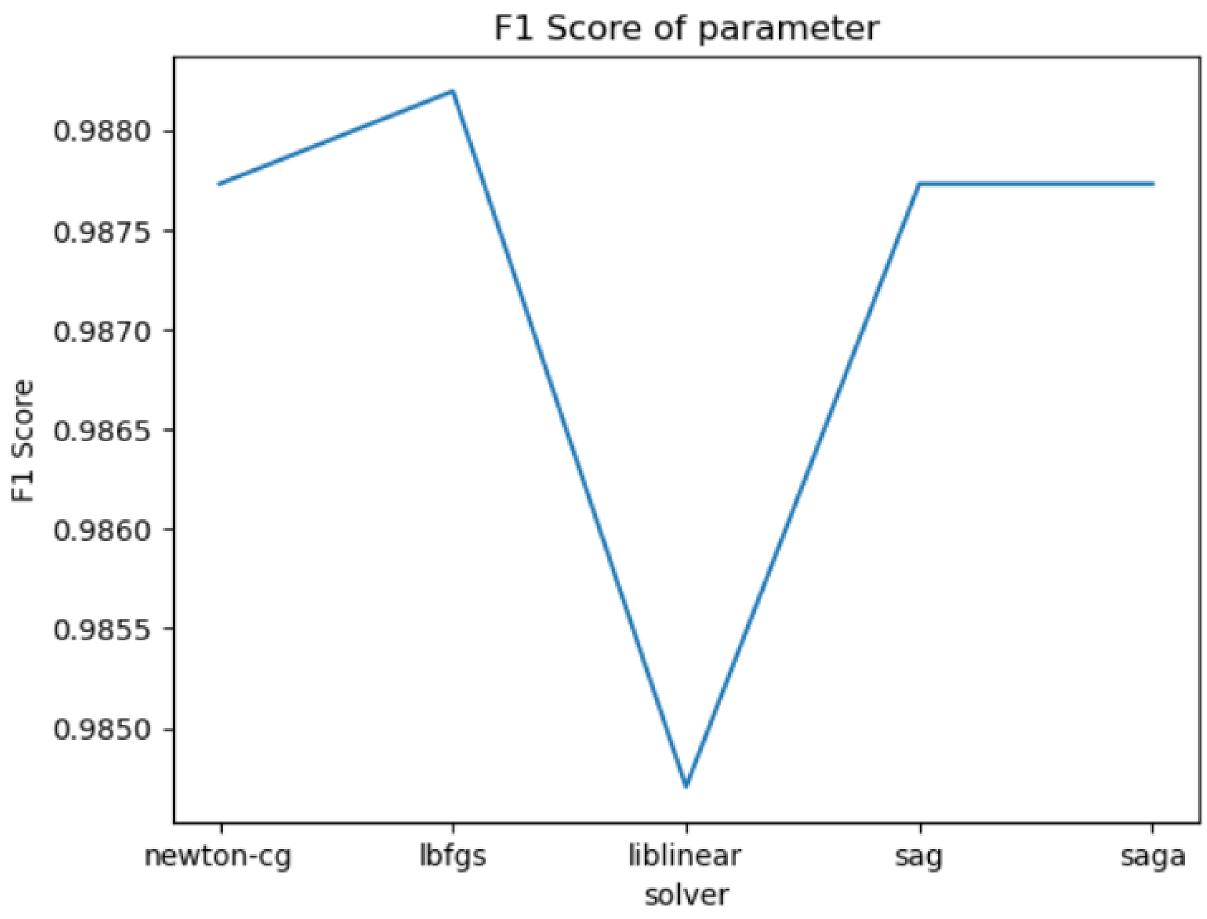
$$\log(\frac{p(X)}{1 - p(X)}) = \beta_0 + \beta_1 X$$

where the left-hand side is called the logit or log-odds function, and p(x)/(1-p(x)) is called odds.
The odds signify the ratio of the probability of success to the probability of failure. Therefore, in Logistic Regression, the linear combination of inputs is mapped to the log (odds) which is the output being equal to 1.

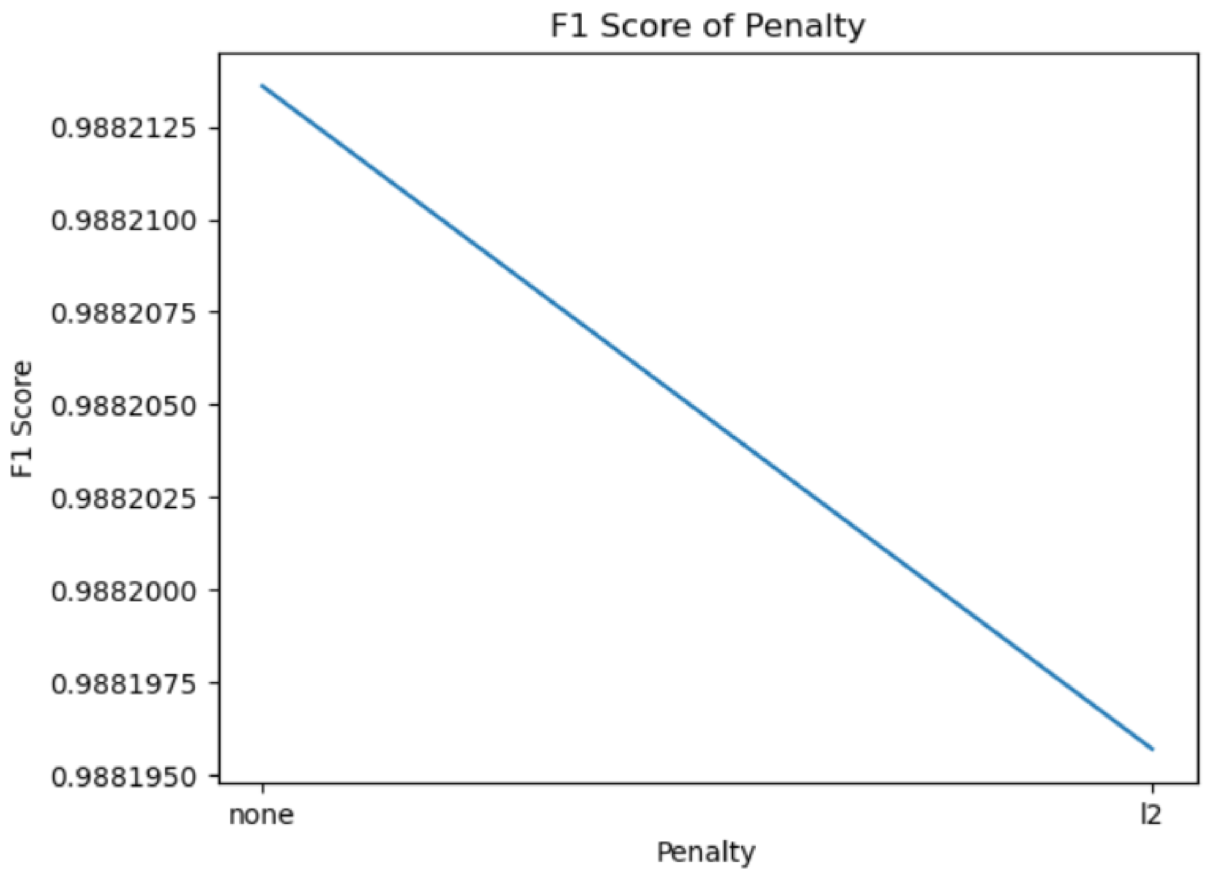
Then we are tuning hyperparameter of this model to choose good parameter set to improve performance of model:



So you can see with C=10,we have best performance so we decided to keep the rbf kernel and adjust the solver parameter



We choose solver is ‘’lbfgs’ to have best f1_score,then we tune penalty parameter



Solver is not support for penalty ''L1'' so we tune with none and ''L2''

Finally,you can see with C=10,solver=lbfgs and penalty is None,we have best f1 score of logit model,so we decide train model with this parameter set.

3.2.2 Support Vector Machine

Support Vector Machine or SVM is a linear model for classification and regression problem. It can solve linear and non-linear problems and work well for many practical problems. The idea of SVM is simple: The algorithm creates a line or a hyperplane which separates the data into classes. From now, we present mainly linear classification.

Linear separability assumption: there exists a hyperplane (of linear form) that well separates the two classes.

SVM finds a hyperplane of the form:

$$f(x) =< w \cdot x > +b$$

where w is the weight vector, b is a real number (bias), $< w \cdot x >$ or $< w,x >$ denote the inner product of two vectors.

For each x_i, we have:

$$y_i = \begin{cases} 1 \text{ if} < w, x_i > +b \geq 0 \\ -1 \text{ if} < w, x_i > +b < 0 \end{cases}$$

The hyperplane (H_0) which separates the positive from negative class is of the form $< w,x > +b = 0$. This equation is also known as the *decision boundary/surface*. But in practice, there will be infinitely many separating hyperplanes that satisfy the decision boundary equation. Then, SVM will select the hyperplane with max margin.

We define two parallel marginal hyperplanes as follows:

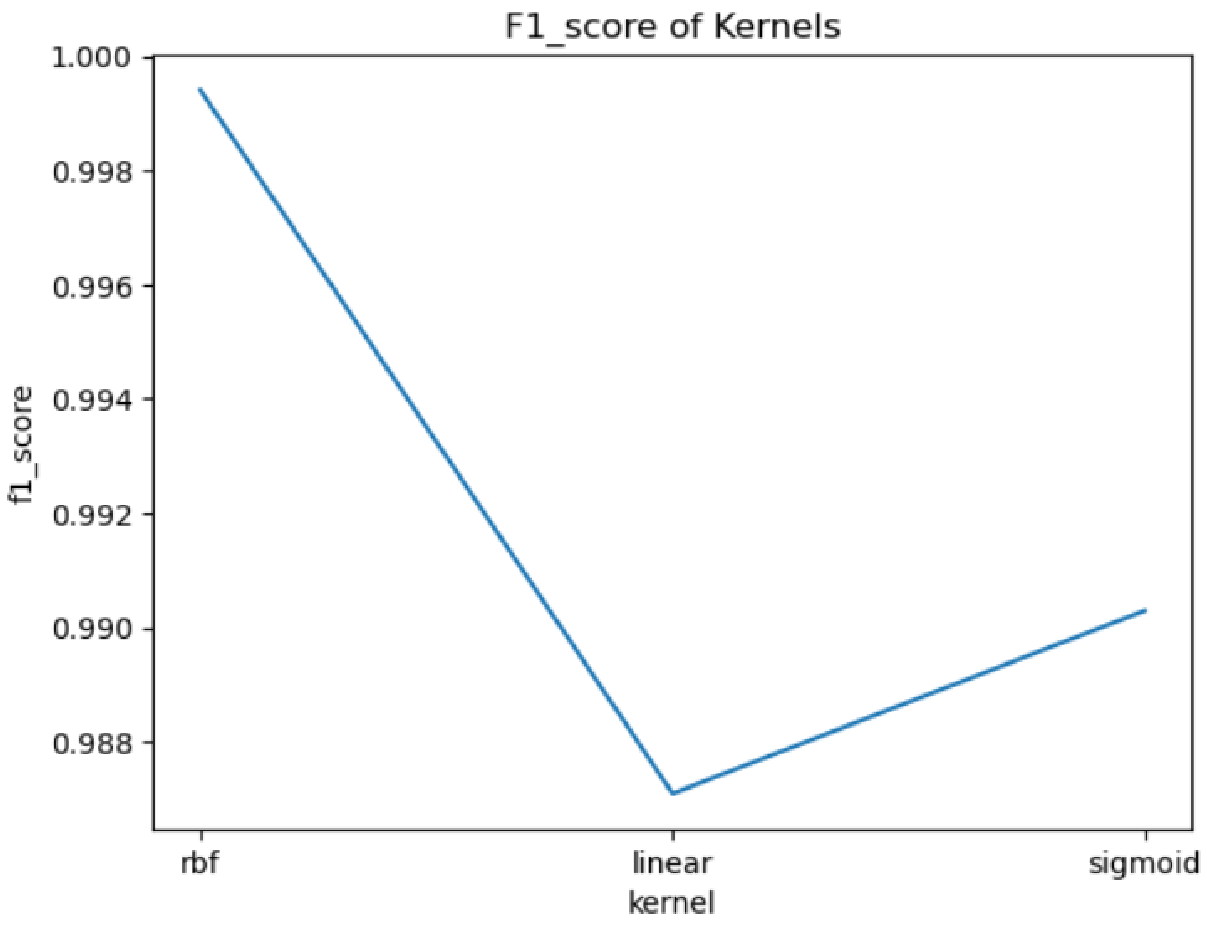
- H_+ crosses x_+ and is parallel with H_0: $< w,x^* > +b = 1$
- H_- crosses x_- and is parallel with H_0: $< w,x^* > +b = -1$
- $(x_+,1)$ in positive class and $(x_-,1)$ in negative class which are closest to the separating hyperplane H_0.

Margin is defined as the distance between the two marginal hyperplanes. $(d_+ + d_-)$ is the margin where d_+ be the distance from H_0 to H_+, d_- be the distance from H_0 to H_-.

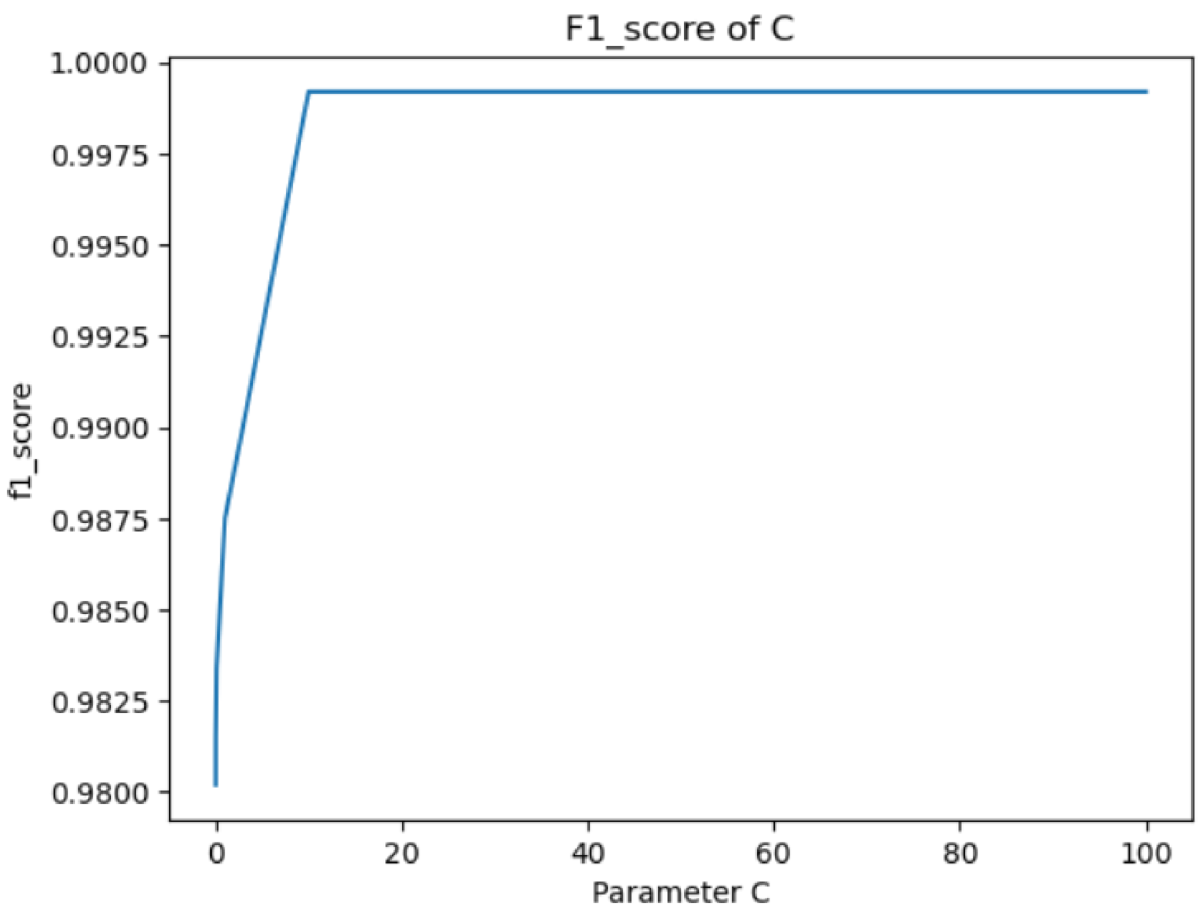
For many problems, our linear separability assumption does not hold, we cannot apply Linear SVM as usual, but the idea of Non-linear SVM solve this:

- Step 1: Transform the input into another space, which often has higher dimensions, so that the projection of data is linearly separable.
- Step 2: Use Linear SVM in the new space.

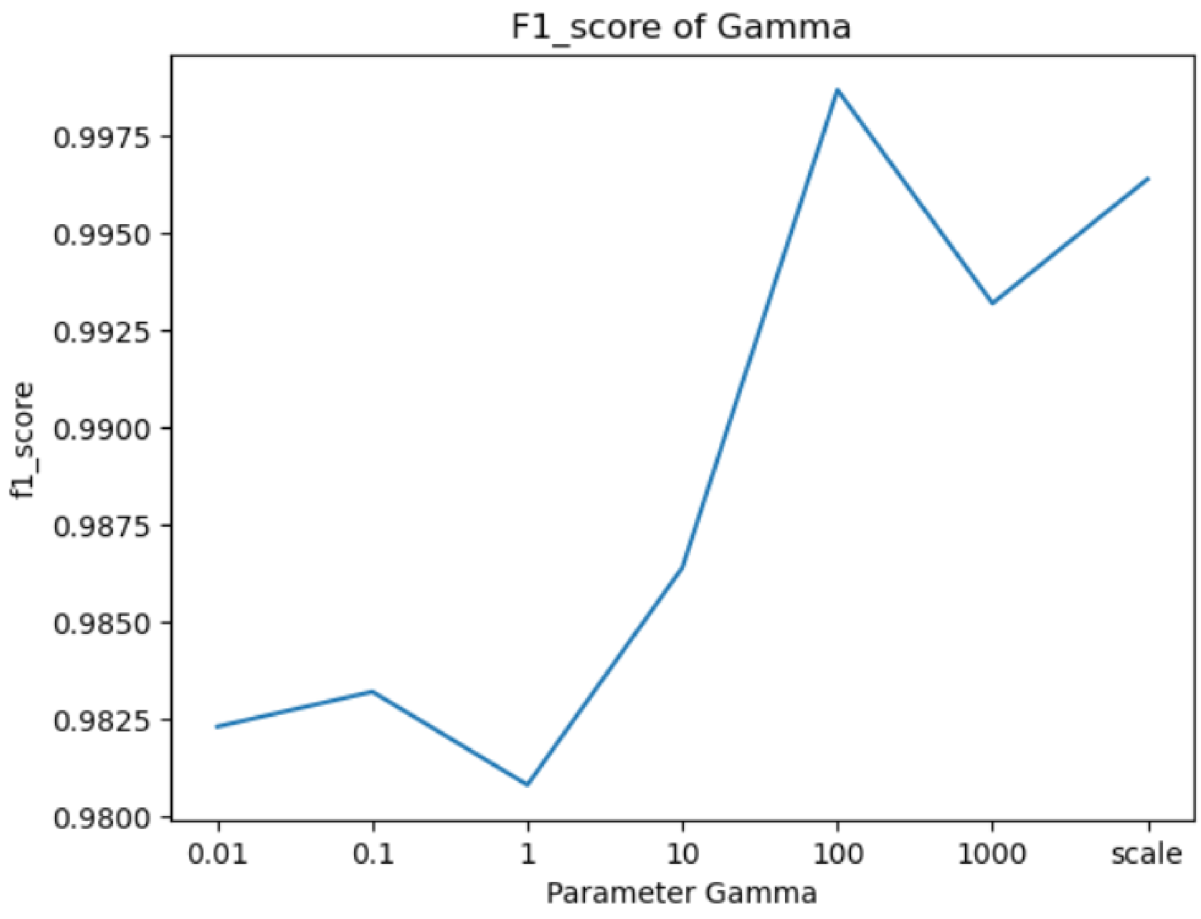
Then we are tuning hyperparameter of this model to choose good parameter set to improve performance of model:



So,you can see with kernel = 'rbf',we have best performance so we decided to keep the rbf kernel and adjust the C parameter



We choose C=10 to have best f1_score,then we tune Gamma parameter(parameter is specified for kernel rbf)



Finally,you can see with kernel=rbf,C=10 and Gamma=100,we have best f1 score of svm model,so we decide train model with this parameter set

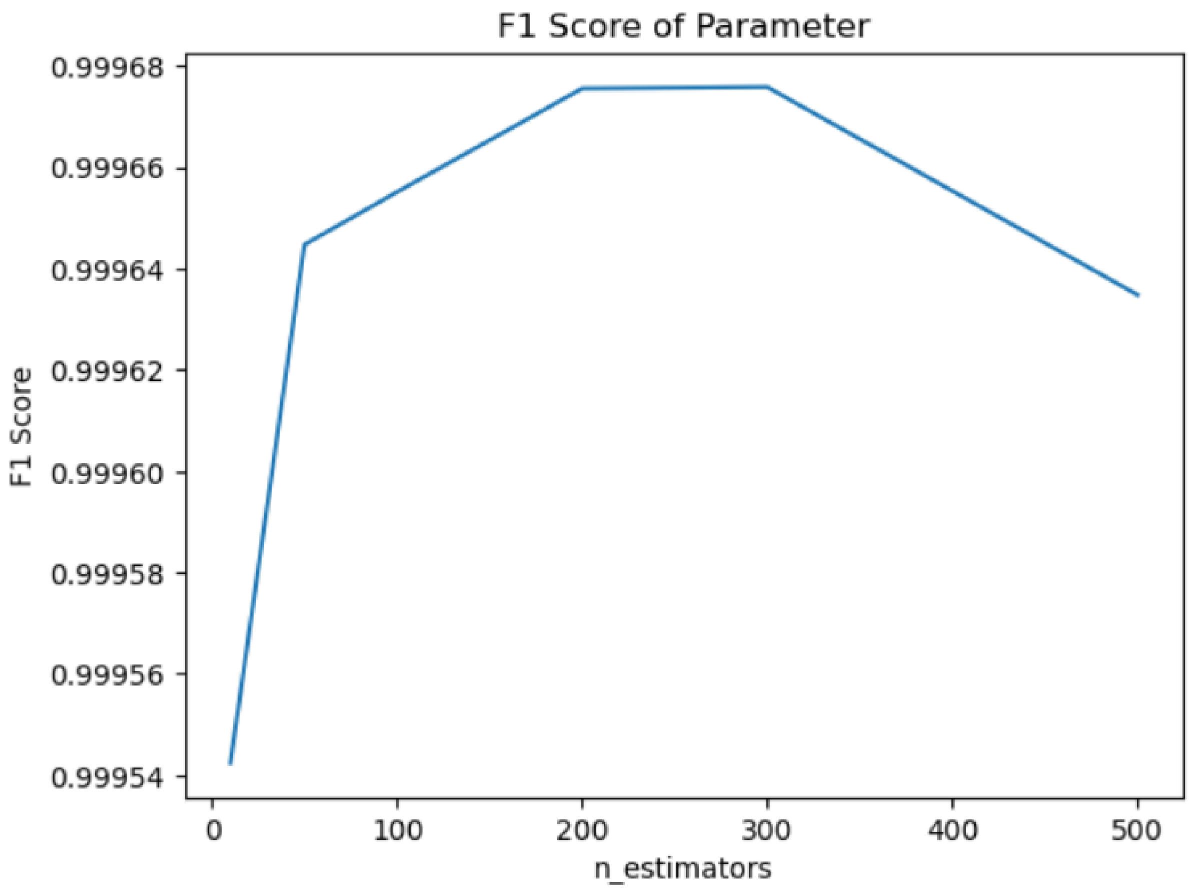
3.2.3 Random Forest

Random forest, like its name implies, consists of a large number of individual decision trees. The logic behind the Random Forest model is that multiple uncorrelated models (the individual decision trees) perform much better as a group than they do alone. When using Random Forest for classification, each tree gives a classification or a vote. The forest will choose the classification with the majority of the votes.

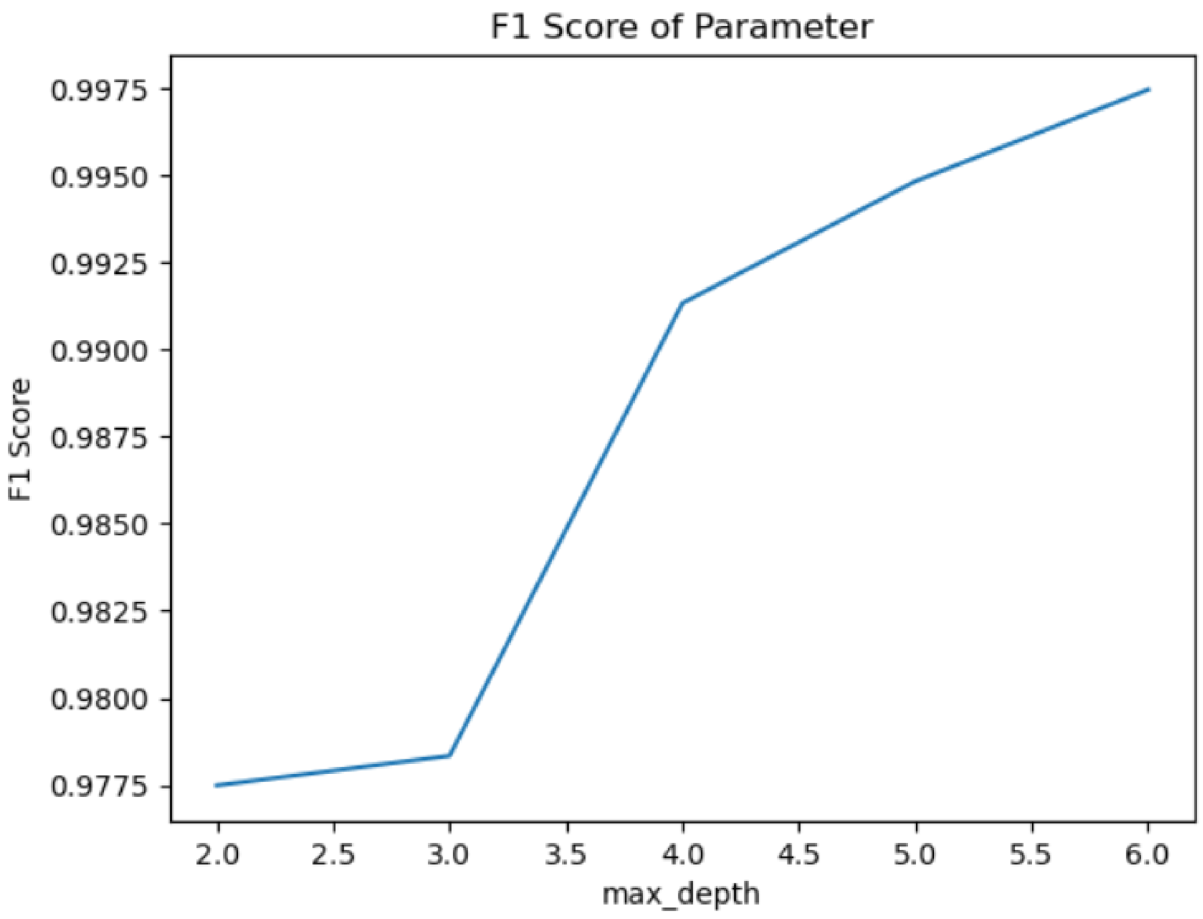
Any Random Forest Model has these three basic ingredients. The first ingredient is **randomization and no pruning**. For each tree and at each node, we select randomly a subset of attributes, find the best split, and then grow appropriate subtrees. Pruning is a technique to avoid overfitting of Decision Tree models, but this technique will not be used in Random Forest models, every tree will be grown to its largest size. The next is a **combination**. Each prediction later is made by taking the average of all predictions of individual trees. In more detail, when using Random Forest for regression, the forest picks the average of the outputs of all trees. In classification, each individual tree in the random forest spits out a class prediction and the class with the most votes becomes our model's prediction. Finally, Random Forest is usually trained using the **bagging** method. The bagging method is a type of ensemble machine learning algorithm called Bootstrap Aggregation. Using the bagging method, the training set for each tree is generated by sampling (with replacement) from the original data.

Random Forest can be implemented easily and efficiently. Figure Figure **??** illustrates one of many ways to implement Random Forest. One more thing is that Random Forest also can work with problems of very high dimensions, without overfitting.

Then we are tuning hyperparameter of this model to choose good parameter set to improve performance of model:



So you can see with number of trees are 300,we have best performance so we decided to keep the n_estimators=300 and adjust the max depth parameter

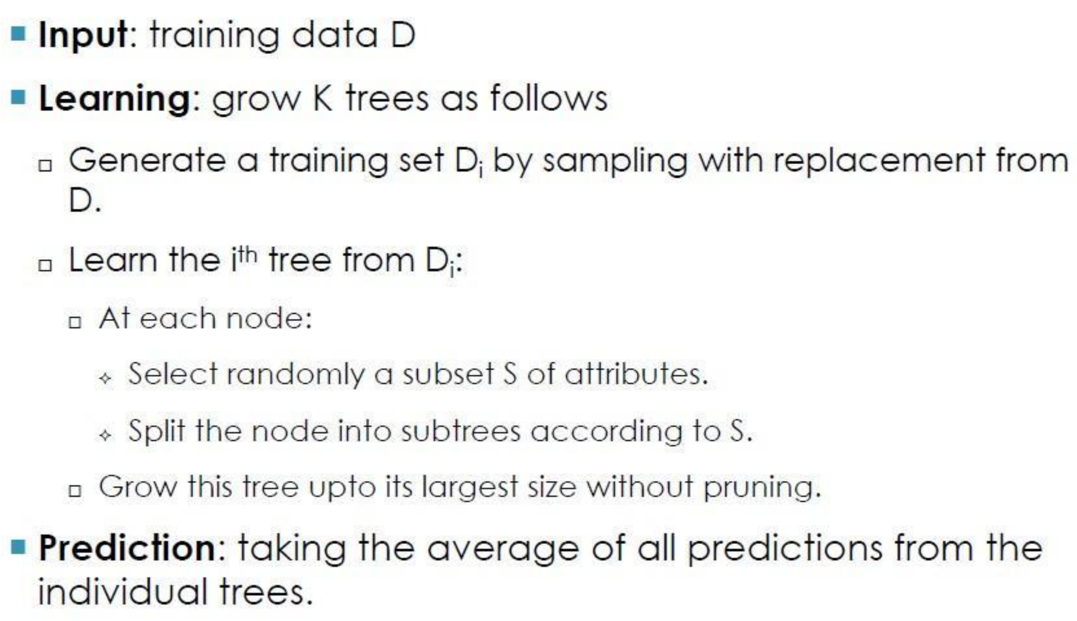


Finally,you can see with number of trees are 300,max depth is 6 we have best f1 score of Random Forest model,so we decide train model with this parameter set.

3.2.4 XGBoost (Gradient Boosting)

Similar to Random Forest Classifier, Adaboost is also an ensemble classifier. Adaboost classifiers combine weak classifier algorithms to form strong classifiers. A single algorithm may classify the objects poorly. But if we combine multiple classifiers with a selection of training sets at every iteration and assign the right amount of weight in final voting, we can have a good accuracy score for the overall classifier. Basically, Adaboost,

1. Retrains the algorithm iteratively by choosing the training set based on accuracy of previous training.
2. The weight-age of each trained classifier at any iteration depends on the accuracy achieved.



- **Input**: training data D
- **Learning**: grow K trees as follows
  - Generate a training set D_i by sampling with replacement from D.
  - Learn the i^{th} tree from D_i:
    - At each node:
      - Select randomly a subset S of attributes.
      - Split the node into subtrees according to S.
    - Grow this tree upto its largest size without pruning.
- **Prediction**: taking the average of all predictions from the individual trees.

Each weak classifier is trained using a **random subset** of the overall training set, but the random subset is not 100% random. After training a classifier at any level, Adaboost assigns weight to each training item. Misclassified item is assigned higher weight so that it appears in the training subset of the next classifier with higher probability. After each classifier is trained, the weight is assigned to the classifier as well based on accuracy. More accurate classifier is assigned a higher weight so that it will have more impact in the final outcome.

A classifier with 50% accuracy is given a weight of zero, and a classifier with less than 50% accuracy is given negative weight.

Let's look at the mathematical formula and parameters

$$H(x) = \text{sign}\left(\sum_{t=1}^{T} \alpha_t h_t(x)\right)$$

where $h_t(x)$ is the output of weak classifier t for input x, α_t is calculated by:

$$\alpha_t = \frac{1}{2}\ln\left(\frac{1-E}{E}\right),$$

E is the error rate

Initially, all the input training examples had equal weightage. After weak classifier is trained, we update the weight of each training example with following formula:

$$D_{t+1}(i) = \frac{D_t(i)e^{-\alpha_t y_i h_t(x_i)}}{Z_t}$$

D_t is weight at the previous level. We normalize the weights by dividing each of them by the sum of all the weights, Z_t.

In the case of incorrect classification, the exponential term became larger than 1, and in the case of correct classification, the exponential term became below 1. Therefore, incorrect classification would receive higher weights, prompting our classifiers to pay more attention to them in the next iteration, while the opposite case of correct classification would result in the converse.

We continue the iteration until the training error achieved is low enough. We then take the final prediction by adding up the weighted prediction of every classifier.

4 Practical Result

4.1 Evaluation Metrics

In our project,in order to evaluate the effectiveness of the models we tried to use different metrics[4] for evaluating each model rigorously such as Accuracy score, Precision score, Recall score, F1-score because of their distinctive advantages:

- Accuracy score: The metric allows us to have a big picture of the correct percentage in our prediction. However, it would be inappropriate for imbalanced-class distributions[5] like this problem. • Precision score: The metric summarizes the fraction of examples assigned to the positive class that belongs to the positive class. • Recall score: The metric summarizes how well the positive class was predicted over the total number of actual instances of this class.
- F1-score: The metric is a combination of Precision and Recall metrics, which seeks the balance of both concerns.
- Macro average accuracy/precision/recall score: The metric is measured by taking an average of all the same metrics for each label class which would help us to identify whether class labels are biased or not.

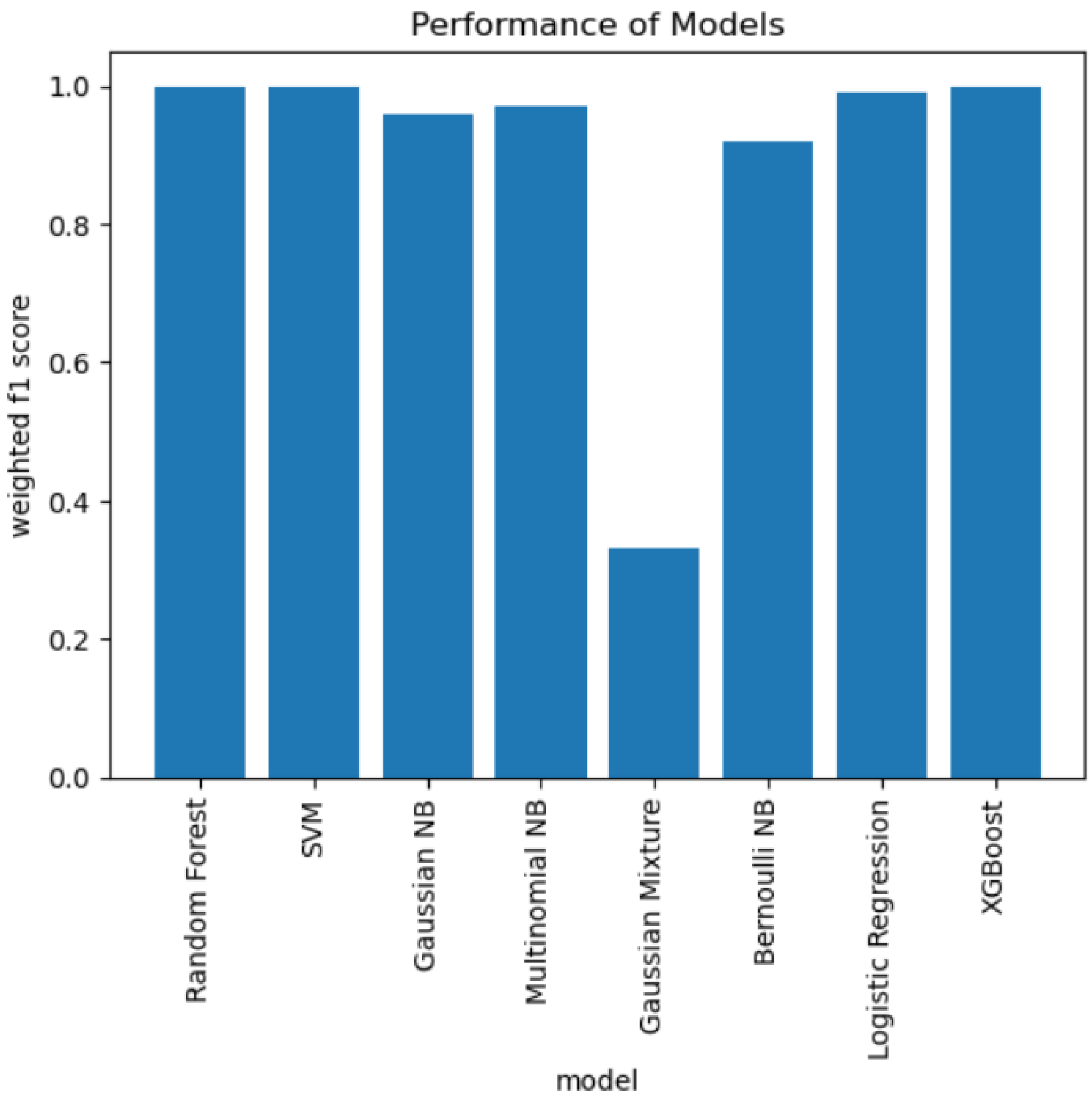
As our project is about network attacks detection, we need to have a specific concern about recall score for some "bad" labels as it is much more important to prevent defective connections from computers to our server.

4.2 Result Table

By using scikit-learn[6] library, we have implemented all models and above methods and got the follow results

Model	Accuracy	Macro Avg Precision	Macro Avg Recall	Macro Avg F1-score
Gaussian Naive Bayes	0.97	0.74	0.66	0.68
Multinomial Naive Bayes	0.97	0.71	0.65	0.65
Gaussian Mixture Model	0.22	0.31	0.33	0.17
Bernoulli Naive Bayes	0.93	0.94	0.58	0.60
Logistic Regression	0.99	0.91	0.88	0.89
Support Vector Machine	1.00	0.96	0.92	0.95
Random Forest	1.00	0.99	0.96	0.97
XGBoost	1.00	1.00	0.99	1.00

Result of different models in terms of different metrics



Weighted F1 Score of Different Models

Since the number of output classes is quite different, we decided to use the weighted average f1 score as the metric to arrive at the final assessment of the model's performance.

The table shows the performance of diverse models by giving figures of different evaluation metrics. It’s noticeable that the scores of Support Vector Machine ,Random Forest and XGBoost were considerably high and especially, they reached the perfect state by having the accuracy score equal to 1. These models were not the only ones that had really high accuracy since the rest models except Gaussian Mixture Model, had nearly equal correctness but disparate precision, recall, and F1-score which resulted in different performances.

Support Vector Machine, Random Forest and XGBoost are the most effective models because not only possess the highest accuracy scores, the remaining numbers are still relatively large, approximately 1.0. Speaking of recall, Support Vector Machine, Random Forest and XGBoost are still holding their own. Also models like Gaussian Naïve Bayes,Multinomial Naïve Bayes,Bernoulli Naïve Bayes and Logistic Regression also have very good performance, that's because the distribution in each feature corresponding to a given class is represented quite well with the hypothesis posed about the distribution of those models. The mixed Gaussian model doesn't seem to fit the solution very well, it's only about 0.22 and its accuracy is about 017->0.33. The reason for this is because the nature of our data is actually 5 classes, by combining the classes with a very small number we somehow accidentally broke the original structure of the output data layer, the clusters that were supposed to be different were combined into 1, which makes the clustering model like Gaussian Mixture Model have bad results.

5 Conclusion

So far, we have successfully solved network attacks detection by using different techniques from exploratory data analysis to modeling and achieved the best result on the XGBoost which has overall accuracy 100%, macro average f1_score 97% using the KDD Cup 99 dataset.

Although the dataset has been considered as a benchmark for network attacks detection problems for decades, it is quite outdated as it was released in the year 1999. It is also a suitable reason why we could achieve such a surprising result with some state-of-the-art techniques and models.

For future development, we would like to use a problem-related dataset involving time series as now the network attacks are hardly spotted by not using the dependence on time.

6. References

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