Import Libraries

In [1]:

```
import pandas as pd
import numpy as np
import sklearn
import matplotlib.pyplot as plt
import seaborn as sns
import time
import warnings
warnings.filterwarnings('ignore')
```

In [2]:

```
dataSet = pd.read_csv('data/nUsersCreditCardTxs.csv')
```

In [3]:

```
dataSet.head()
```

Out[3]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	...	-0.01
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.255425	...	-0.22
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514654	...	0.24
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387024	...	-0.10
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817739	...	-0.00

5 rows × 31 columns

Notice that the variables are PCA transformed. Due to confidentiality issues the data set available online isn't having the actual feature names. Only Time and Amount are readable ones. While Amount is the total transaction amount, the Time column is the number of seconds elapsed between the transaction in consideration and the very first transaction of the dataset.

In [4]:

```
dataSet.info(verbose=True, show_counts=True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 284807 entries, 0 to 284806
Data columns (total 31 columns):
 #   Column  Non-Null Count   Dtype  
---  ------  --------------   -----  
 0   Time    284807 non-null  float64
 1   V1      284807 non-null  float64
 2   V2      284807 non-null  float64
 3   V3      284807 non-null  float64
 4   V4      284807 non-null  float64
 5   V5      284807 non-null  float64
 6   V6      284807 non-null  float64
 7   V7      284807 non-null  float64
 8   V8      284807 non-null  float64
 9   V9      284807 non-null  float64
 10  V10     284807 non-null  float64
 11  V11     284807 non-null  float64
 12  V12     284807 non-null  float64
 13  V13     284807 non-null  float64
 14  V14     284807 non-null  float64
 15  V15     284807 non-null  float64
 16  V16     284807 non-null  float64
 17  V17     284807 non-null  float64
 18  V18     284807 non-null  float64
 19  V19     284807 non-null  float64
 20  V20     284807 non-null  float64
 21  V21     284807 non-null  float64
 22  V22     284807 non-null  float64
 23  V23     284807 non-null  float64
 24  V24     284807 non-null  float64
 25  V25     284807 non-null  float64
 26  V26     284807 non-null  float64
 27  V27     284807 non-null  float64
 28  V28     284807 non-null  float64
 29  Amount  284807 non-null  float64
 30  Class   284807 non-null  int64  
dtypes: float64(30), int64(1)
memory usage: 67.4 MB
```

Data is clean as there aren't any null values

Data set limitation

In [5]:

```
dataSet['Class'].value_counts()
```

Out[5]:

```
0    284315
1       492
Name: Class, dtype: int64
```

Class with value 1 indicate fradulent transaction and Class with value 0 indicate a legitimate transaction. The data set has only 492 fradulent transaction which is 0.17% of the data set. This is a very imbalanced data set.

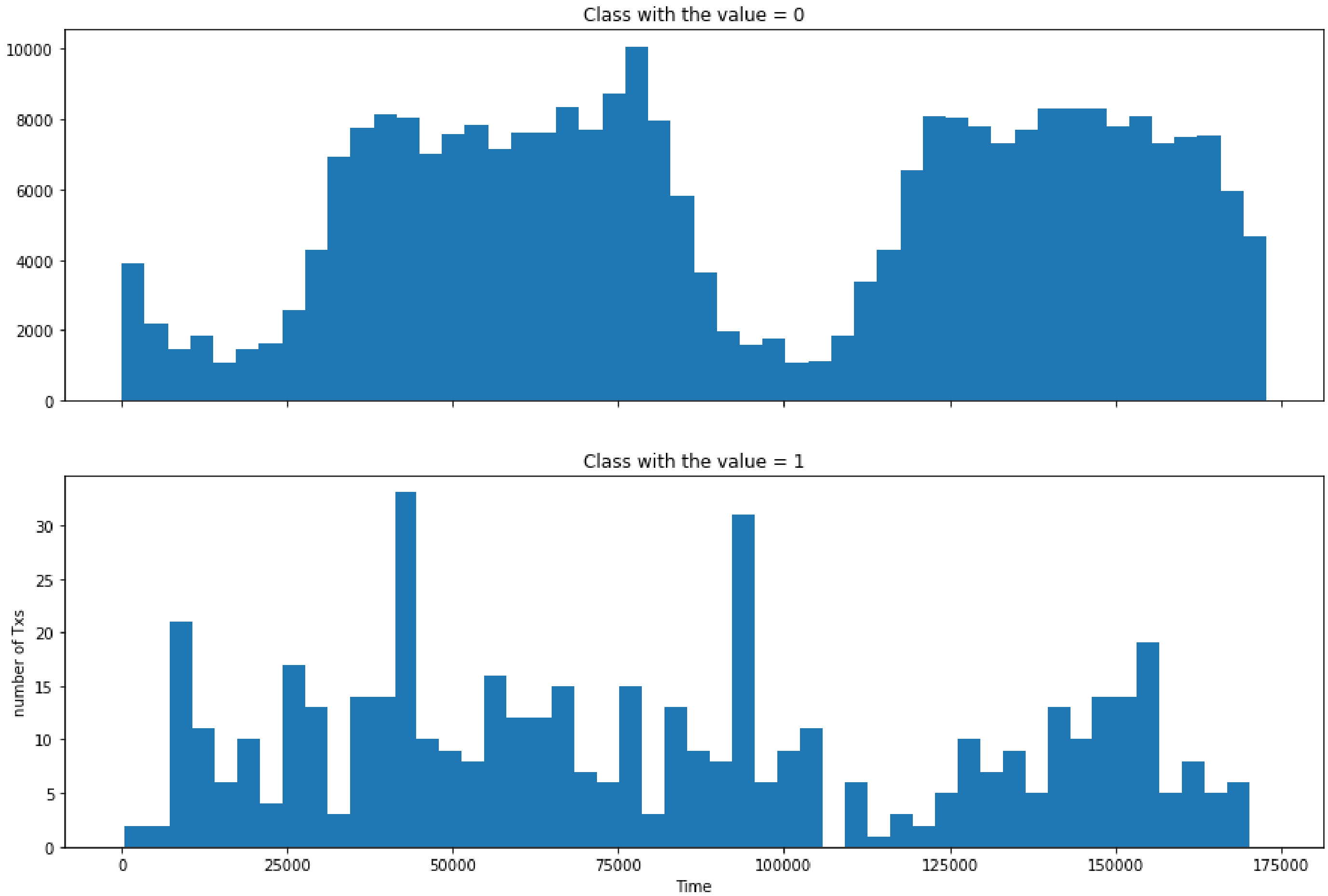
Data Visualization

Histogram

In [6]:

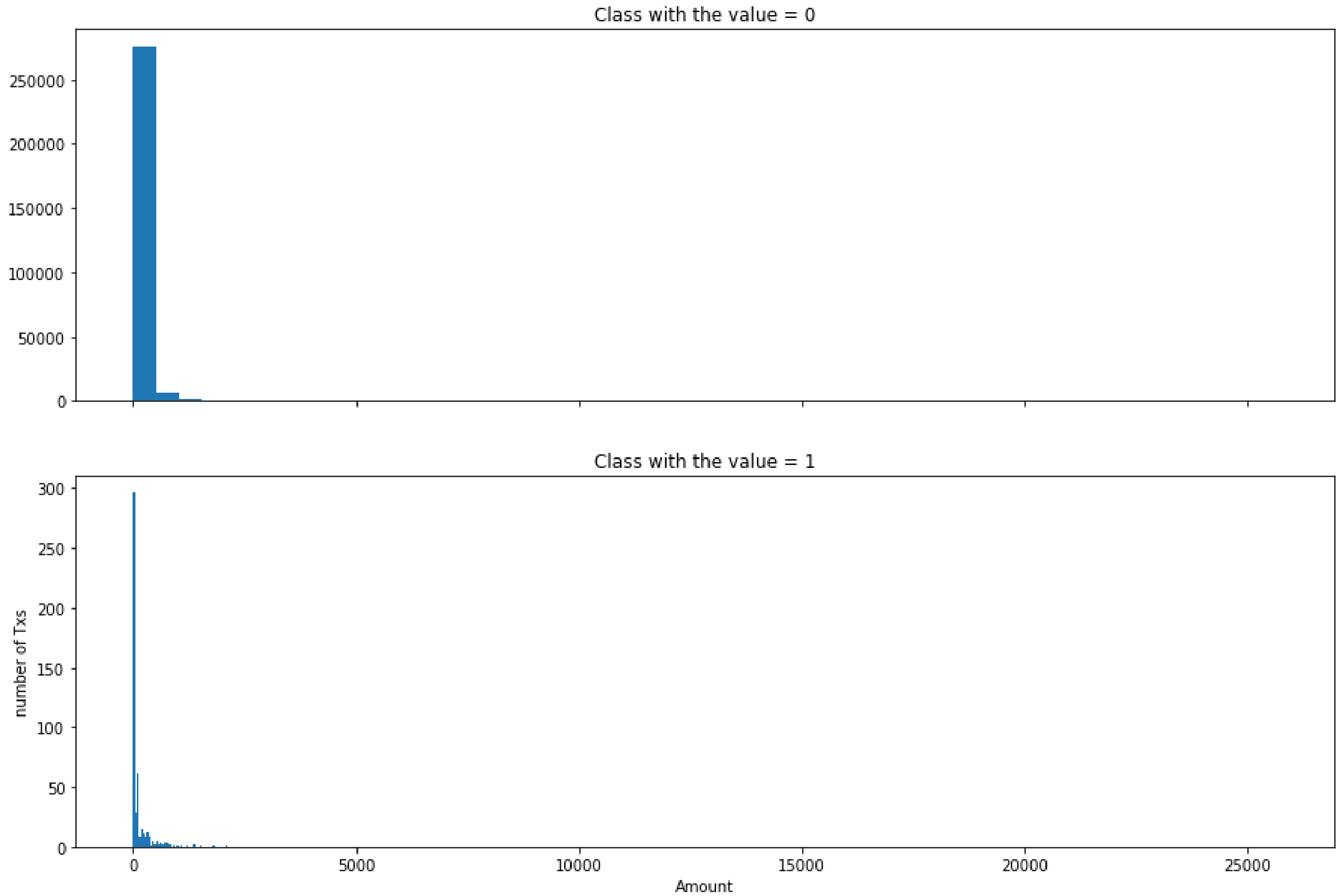
```
classValues = dataSet['Class'].value_counts().index

fig, (timeClass0Fig, timeClass1Fig) = plt.subplots(2, 1, sharex=True, figsize=(15, 10))

timeClass0Fig.hist(dataSet['Time'][dataSet['Class']==classValues[0]], bins=50)
timeClass0Fig.set_title('Class with the value = ' + str(classValues[0]))
```

```
timeClass1Fig.hist(dataSet['Time'][dataSet['Class']==classValues[1]], bins=50)
timeClass1Fig.set_title('Class with the value = ' + str(classValues[1]))

plt.xlabel('Time')
plt.ylabel('number of Txs')

plt.show()
```



In [7]:

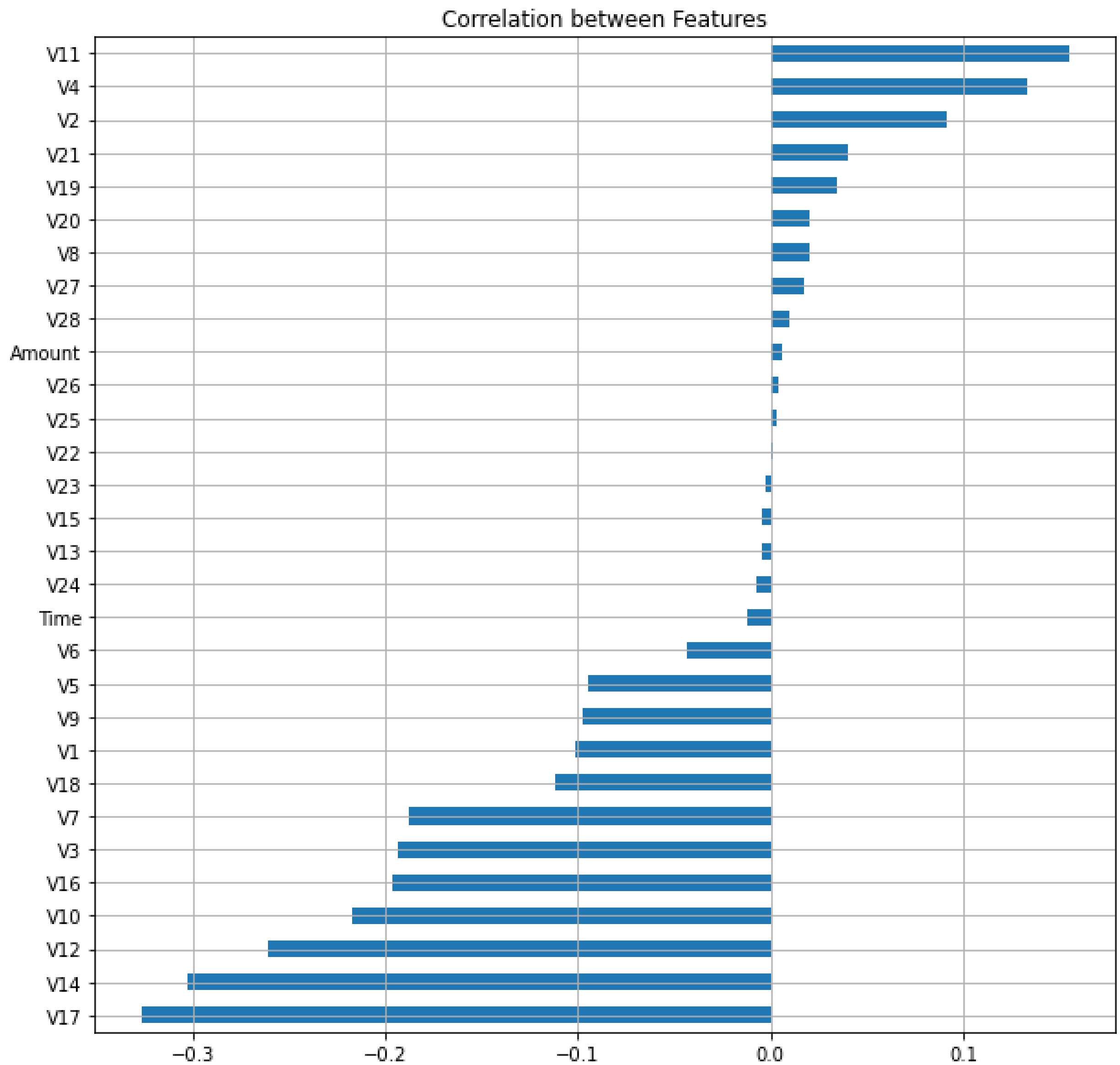
```
fig, (timeClass0Fig, timeClass1Fig) = plt.subplots(2, 1, sharex=True, figsize=(15, 10))

timeClass0Fig.hist(dataSet['Amount'][dataSet['Class']==classValues[0]], bins=50)
timeClass0Fig.set_title('Class with the value = ' + str(classValues[0]))

timeClass1Fig.hist(dataSet['Amount'][dataSet['Class']==classValues[1]], bins=50)
timeClass1Fig.set_title('Class with the value = ' + str(classValues[1]))

plt.xlabel('Amount')
plt.ylabel('number of Txs')

plt.show()
```



Correlation

In [8]:

```
plt.figure(figsize=(10,10))
corr = dataSet.corr()['Class'].sort_values().drop('Class')
corr.plot(kind='barh')
plt.title('Correlation between Features')
plt.grid(True)
plt.show()
```



Separating the data into featured and dependent variable

In [9]:
```
df = dataSet[dataSet['Class'] == 1]
df1 = dataSet[dataSet['Class']== 0]
df1.drop(df1.index[2000: ],0,inplace=True)
nUsersCreditCardTxs = pd.concat([df, df1], axis=0)
```

In [10]:
```
nUsersCreditCardTxs.drop(['V11','V4','V2','V21','V19','V20','V8','V27','V28','Amount','V

x = nUsersCreditCardTxs.iloc[: , :-1].values
y = nUsersCreditCardTxs.iloc[: , -1].values
```

In [11]:
```
from sklearn.model_selection import train_test_split

x_train,x_test,y_train,y_test= train_test_split(x,y, test_size=0.2, stratify=y, random_s
```

In [12]:
```
from sklearn.preprocessing import StandardScaler

standardScaler=StandardScaler()
x_train=standardScaler.fit_transform(x_train)
x_test=standardScaler.transform(x_test)
```

Model building

Model 1 - Logistic Regression

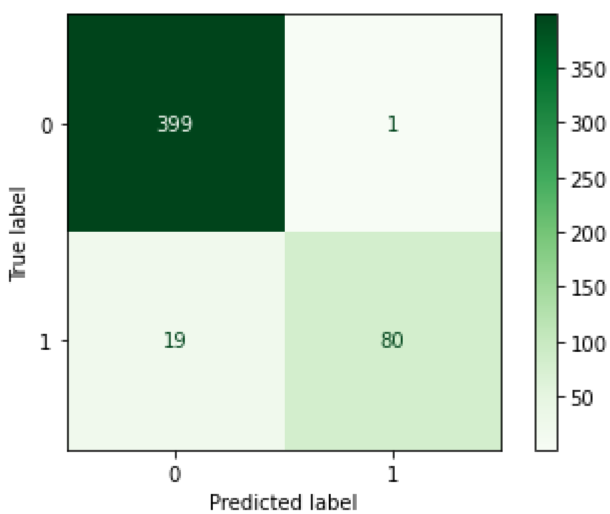
In [13]:
```
from sklearn.linear_model import LogisticRegression

lrModel = LogisticRegression()
lrModel = lrModel.fit(x_train,y_train)
y_pred = lrModel.predict(x_test)
```

In [14]:
```
from sklearn.metrics import accuracy_score, confusion_matrix

accuracyLR = accuracy_score(y_test,y_pred)
confusionMatrixLR = confusion_matrix(y_test,y_pred)
```

In [15]:
```
print(f"Accuracy is {accuracyLR*100}")
print("Confusion Matrix is ")
print(confusionMatrixLR)
```

```
Accuracy is 95.99198396793587
Confusion Matrix is
[[399   1]
 [ 19  80]]
```

In [16]:
```
from sklearn.metrics import plot_confusion_matrix

plot_confusion_matrix(lrModel, x_test, y_test, cmap=plt.cm.Greens)
plt.show()
```



Model 2 - Linear SVM (Support Vector Machine)

In [17]:
```
from sklearn import svm

svmModel = svm.SVC(kernel='linear')
```

In [18]:
```
svmModel.fit(x_train, y_train)
```

Out[18]:
```
SVC(kernel='linear')
```

In [19]:

```
y_pred = svmModel.predict(x_test)
```

In [20]:

```
accuracySVM = accuracy_score(y_test,y_pred)
confusionMatrixSVM = confusion_matrix(y_test,y_pred)
```

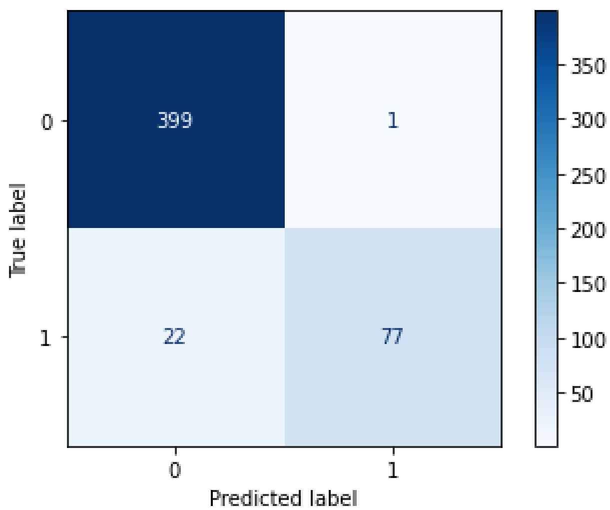
In [21]:

```
print(f"Accuracy is {accuracySVM*100}")
print("Confusion Matrix is ")
print(confusionMatrixSVM)
```

```
Accuracy is 95.39078156312625
Confusion Matrix is 
[[399   1]
 [ 22  77]]
```

In [22]:

```
plot_confusion_matrix(svmModel, x_test, y_test, cmap=plt.cm.Blues)
plt.show()
```



Model 3 - Decision Tree

In [23]:

```
from sklearn import tree

dtModel = tree.DecisionTreeClassifier()
dtModel = dtModel.fit(x_train,y_train)
y_pred = dtModel.predict(x_test)
```

In [24]:

```
accuracyDt=accuracy_score(y_test,y_pred)
confusionMatrixDt=confusion_matrix(y_test,y_pred)
```

In [25]:

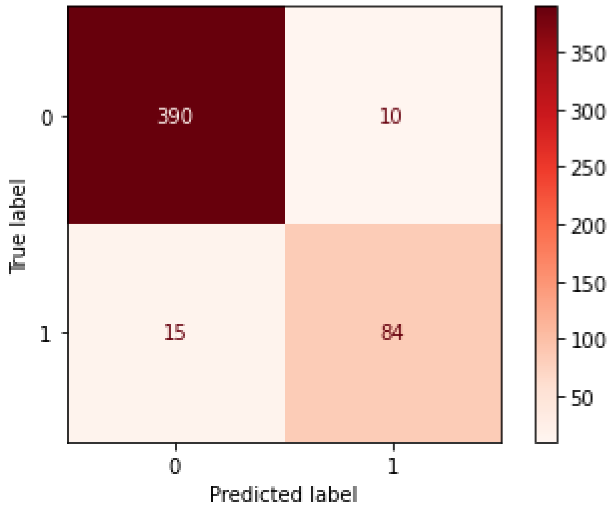
```
print(f"Accuracy is {accuracyDt*100}")
print("Confusion Matrix is ")
print(confusionMatrixDt)
```

```
Accuracy is 94.98997995991984
Confusion Matrix is 
[[390  10]
 [ 15  84]]
```

In [26]:

```
plot_confusion_matrix(dtModel, x_test, y_test,cmap=plt.cm.Reds)
```

```
plt.show()
```



Model 4 - RandomForestClassifier

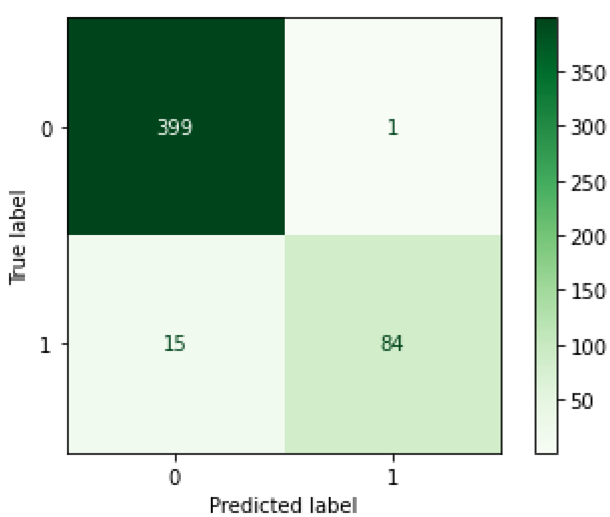
In [27]:
```
from sklearn.ensemble import RandomForestClassifier

rfModel =RandomForestClassifier()
rfModel = rfModel.fit(x_train,y_train)
y_pred = rfModel.predict(x_test)
```

In [28]:
```
accuracyRf=accuracy_score(y_test,y_pred)
confusionMatrixRf=confusion_matrix(y_test,y_pred)
```

In [29]:
```
print(f"Accuracy is {accuracyRf*100}")
print("Confusion Matrix is ")
print(confusionMatrixRf)
```

```
Accuracy is 96.79358717434869
Confusion Matrix is
[[399   1]
 [ 15  84]]
```

In [30]:
```
plot_confusion_matrix(rfModel, x_test, y_test,cmap=plt.cm.Greens)
plt.show()
```



Model 5 - VotingClassifier

In [31]:

```
from sklearn.ensemble import VotingClassifier

vcModel = VotingClassifier(estimators=[('rf', rfModel),('dt', dtModel)], voting='hard')
vcModel = vcModel.fit(x_train,y_train)
y_pred = vcModel.predict(x_test)
```

In [32]:

```
accuracyVC = accuracy_score(y_test,y_pred)
confusionMatrixVC = confusion_matrix(y_test,y_pred)
```

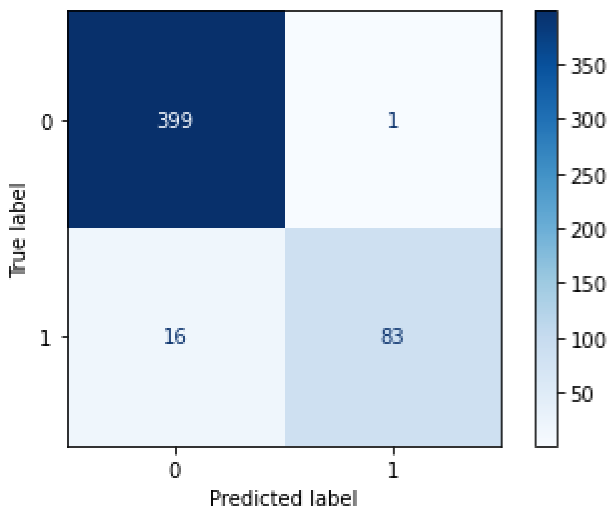
In [33]:

```
print(f"Accuracy is {accuracyVC*100}")
print("Confusion Matrix is ")
print(confusionMatrixVC)
```

```
Accuracy is 96.59318637274549
Confusion Matrix is
[[399   1]
 [ 16  83]]
```

In [34]:

```
plot_confusion_matrix(vcModel, x_test, y_test,cmap=plt.cm.Blues)
plt.show()
```



Model 6 - XGBoost

In [35]:

```
import xgboost as xgb

#xgbModel = xgb.XGBRegressor(objective ='reg:logistic', colsample_bytree = 0.3, learning
#                max_depth = 5, alpha = 10, n_estimators = 10)
xgbModel = xgb.XGBClassifier()
xgbModel = xgbModel.fit(x_train,y_train)
y_pred = xgbModel.predict(x_test)
```

```
[21:24:43] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.5.1/src/lea
rner.cc:1115: Starting in XGBoost 1.3.0, the default evaluation metric used with the obj
ective 'binary:logistic' was changed from 'error' to 'logloss'. Explicitly set eval_metr
ic if you'd like to restore the old behavior.
```

In [36]:

```
accuracyXGB = accuracy_score(y_test,y_pred)
confusionMatrixXGB = confusion_matrix(y_test,y_pred)
```

In [37]:

```
print(f"Accuracy is {accuracyXGB*100}")
print("Confusion Matrix is ")
print(confusionMatrixXGB)
```

```
Accuracy is 96.39278557114228
Confusion Matrix is
[[398   2]
 [ 16  83]]
```

In [38]:

```
plot_confusion_matrix(xgbModel, x_test, y_test,cmap=plt.cm.Reds)
plt.show()
```