Econ 425 Class Project

Table of Contents

In [1]:
```
import numpy as np
from numpy import array
import pandas as pd
import download_data as dl

import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib.pyplot import MultipleLocator

#from conf_matrix import func_confusion_matrix
#import os # package for communicating with operating system
from sklearn.model_selection import train_test_split

from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import RidgeClassifier, SGDClassifier, ElasticNet
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
import sklearn.svm as svm

from sklearn import metrics
from sklearn.metrics import roc_curve, auc, roc_auc_score
from sklearn.metrics import r2_score, confusion_matrix, classification_report
from sklearn.metrics import precision_recall_curve, precision_score, recall_score
from yellowbrick.classifier import ClassificationReport

import random, heapq
import tensorflow as tf
from tensorflow import keras
from keras.models import Sequential
from tensorflow.keras import layers
from keras.layers import Activation, Dense
from sklearn.ensemble import RandomForestClassifier

import warnings
warnings.filterwarnings("ignore")


#os.chdir('/Users/ruyalatif/Desktop/class project/our project')
```

Data Preparation

In [2]:

```python
#load data
df = dl.download_data("creditcard.csv")

names = df.loc[0]
df.columns = names
df = df.iloc[1:]

df.head()

#we could see we need to normalize "Amount" and drop "Time"
```

	Time	V1	V2	V3	V4	V5	V6
1	0	-1.3598071336738	-0.0727811733098497	2.53634673796914	1.37815522427443	-0.338320769942518	0.462387777762292
2	0	1.19185711131486	0.26615071205963	0.16648011335321	0.448154078460911	0.0600176492822243	-0.0823608088155687
3	1	-1.35835406159823	-1.34016307473609	1.77320934263119	0.379779593034328	-0.503198133318193	1.80049938079263
4	1	-0.966271711572087	-0.185226008082898	1.79299333957872	-0.863291275036453	-0.0103088796030823	1.24720316752486
5	2	-1.15823309349523	0.877736754848451	1.548717846511	0.403033933955121	-0.407193377311653	0.0959214624684256

5 rows × 31 columns

In [3]:

```python
# seperate input and output datasets
y = pd.DataFrame(df['Class'].copy())
y=y.astype('int')

X = df.drop(["Time", "Class"], axis=1)

# rescale Feature "Amount"
X['Amount'] = [float(i) for i in X['Amount']]

amount_min = X['Amount'].min()
amount_denom = X['Amount'].max() - amount_min
X['Amount'] = (X['Amount'] - amount_min) / amount_denom


#check again
X.head()
```

	V1	V2	V3	V4	V5	V6	
1	-1.3598071336738	-0.0727811733098497	2.53634673796914	1.37815522427443	-0.338320769942518	0.462387777762292	0.2395
2	1.19185711131486	0.26615071205963	0.16648011335321	0.448154078460911	0.0600176492822243	-0.0823608088155687	-0.0788
3	-1.35835406159823	-1.34016307473609	1.77320934263119	0.379779593034328	-0.503198133318193	1.80049938079263	0.7914
4	-0.966271711572087	-0.185226008082898	1.79299333957872	-0.863291275036453	-0.0103088796030823	1.24720316752486	0.2376
5	-1.15823309349523	0.877736754848451	1.548717846511	0.403033933955121	-0.407193377311653	0.0959214624684256	0.5929

5 rows × 29 columns

Data Visualization

In [4]:
```
df.describe()
```

	Time	V1	V2	V3	V4	V5	V6	V7	
count	284807	284807.000000	284807.000000	284807.000000	284807.000000	284807.000000	284807.000000	284807.000000	284807.00
unique	124592	276176.000000	276176.000000	276176.000000	276176.000000	276176.000000	276176.000000	276176.000000	276176.00
top	163152	2.055797	-0.326668	-2.752041	-0.842316	2.463072	3.173856	-0.432126	0.727706
freq	36	77.000000	77.000000	77.000000	77.000000	77.000000	77.000000	77.000000	77.00000

4 rows × 31 columns

In [15]:
```
print(X.shape)
print(y.shape)
```

```
(284807, 29)
(284807, 1)
```

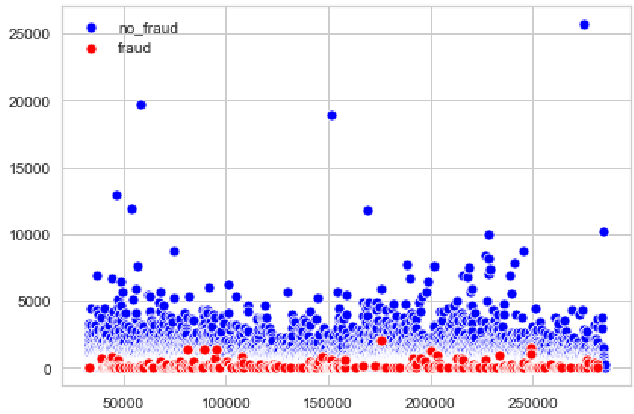
In [5]:
```
#checking null values
df.isnull().sum()
```

```
0
Time      0
V1        0
V2        0
V3        0
V4        0
V5        0
V6        0
V7        0
V8        0
V9        0
V10       0
V11       0
V12       0
V13       0
V14       0
V15       0
V16       0
V17       0
V18       0
V19       0
V20       0
V21       0
V22       0
V23       0
V24       0
V25       0
V26       0
V27       0
V28       0
Amount    0
Class     0
dtype: int64
```

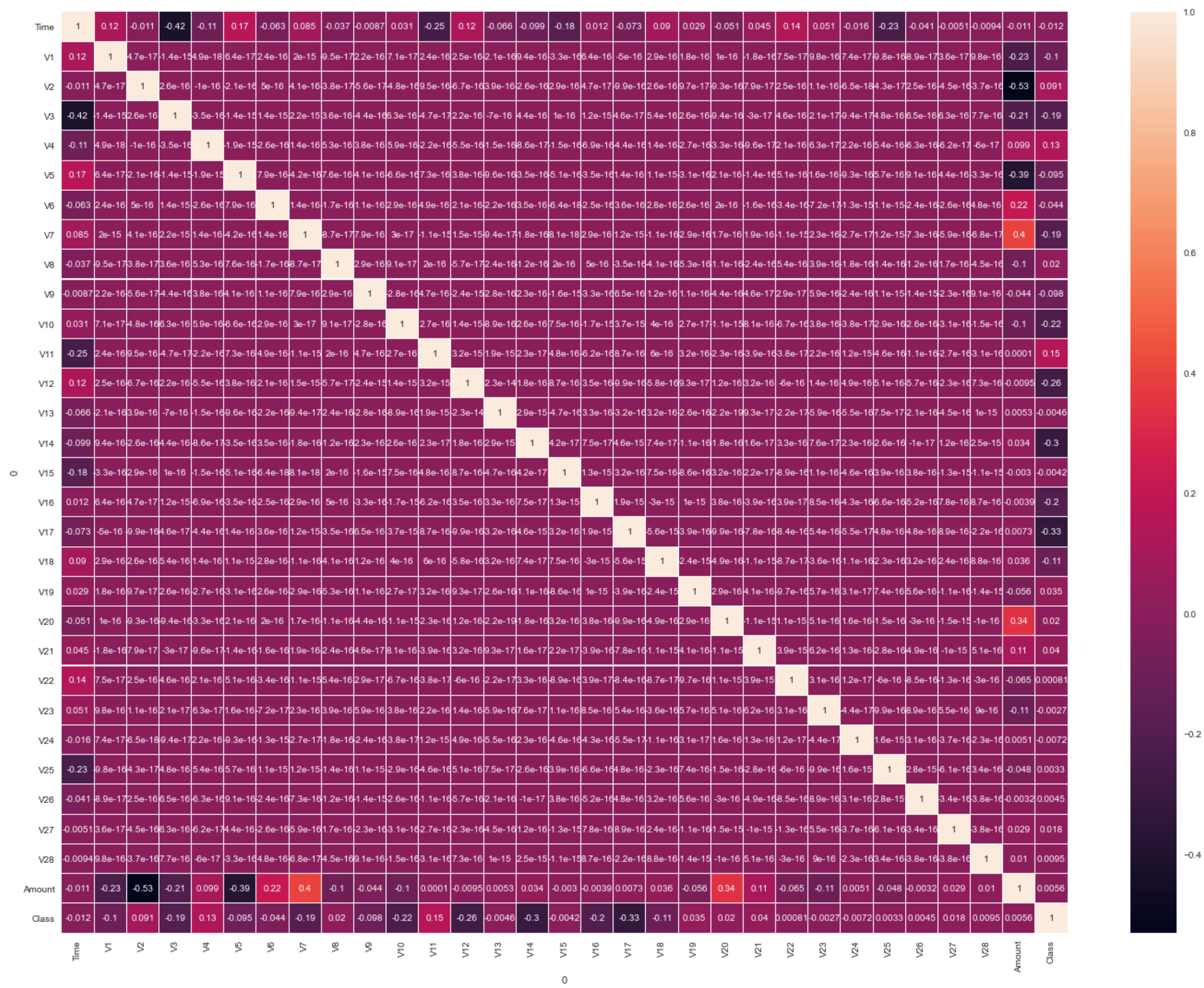
In [4]:
```
#for Class
display(y.groupby(['Class']).size())

#Percentage proportion of fraud class and non-fraud class
fraud = df[df['Class']==1]
no_fraud = df[df['Class']==0]

print("Fraud Cases in our data set : ",len(fraud)*100/len(df)," %")
print("Non Fraud Cases in our data set : ",len(no_fraud)*100/len(df)," %")

# severely imbalanced
```

```
Class
0    284315
1       492
dtype: int64


Fraud Cases in our data set :  0.13693483657353928  %
Non Fraud Cases in our data set :  88.35808108649015  %
```

In [5]:
```
# For amount
#plotting Amount attribute as scatterplot
%matplotlib inline
sns.scatterplot(data=no_fraud['Amount'],color='blue')
sns.scatterplot(data=fraud['Amount'],color='red')
plt.legend(['no_fraud','fraud'])
plt.tight_layout()
```



In [6]:
```python
#Corr Plot
df_copy = df.copy()
df_copy = df_copy.astype('float')

corr = df_copy.corr()
fig, ax = plt.subplots(figsize=(20, 15))

sns.heatmap(corr, xticklabels=corr.columns, yticklabels=corr.columns,
            linewidths=.1, ax=ax, annot=True)
plt.tight_layout()
```



Data Splitting

In [4]:
```python
# split into training and testing datasets
Xtrain, Xtest, Ytrain, Ytest = train_test_split(X,y,test_size=.5, random_state=425)
# split training set again into training and validation set
Xtrain, Xval, Ytrain, Yval = train_test_split(Xtrain,Ytrain,
                                              test_size=.2, random_state=425)
```

In [5]:
```python
df1 = Ytrain.loc[df['Class'].isin(['1'])]
print(len(df1))
```

```
41
```

In [6]:
```python
Xtrain, Xval, Xtest = Xtrain.values, Xval.values, Xtest.values
Ytrain = Ytrain.values.ravel().astype('int')
Yval = Yval.values.ravel().astype('int')
Ytest = Ytest.values.ravel().astype('int')
```

```
In [7]: print(Xtrain.shape) #training samples
        print(Xval.shape) #validation sample to choose the best model
        print(Xtest.shape) #testing sample
```

```
(113922, 29)
(28481, 29)
(142404, 29)
```

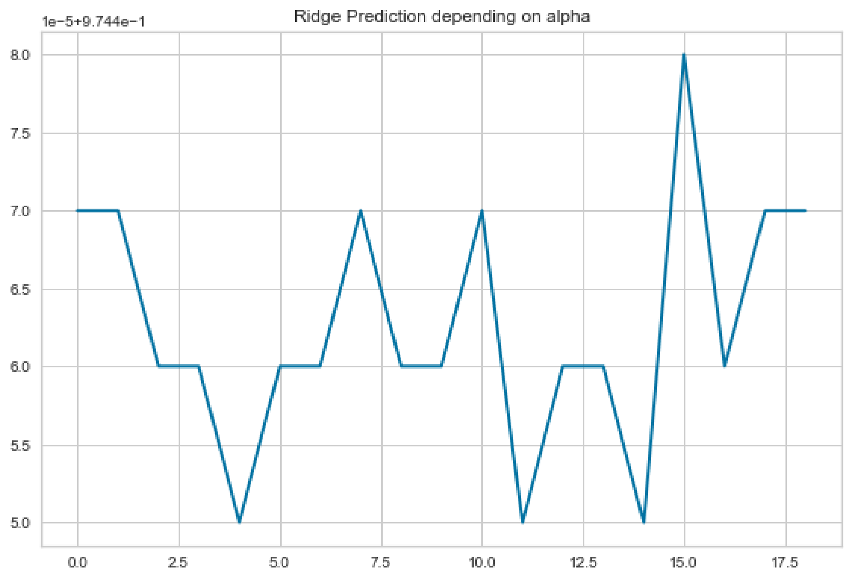
Model Selection

1. Linear Classification

1.1 Ridge Classifier

```
In [8]: ########RidgeClassifier using the sklearn, finding the best learning rate #######
        alpha = np.arange(0.1,2,0.1)
        ridge_score = []

        for a in alpha:
            model_ridge =  RidgeClassifier(alpha=a, solver='saga').fit(Xtrain, Ytrain)
            score_val = model_ridge.decision_function(Xval)
            fpr, tpr, thresholds = roc_curve(Yval, score_val)
            ridge_score.append(np.around(auc(fpr, tpr),5))


        # plot the AUC graph
        plt.plot(ridge_score,lw=2)
        plt.title("Ridge Prediction depending on alpha", size = 12)
        plt.tight_layout()

        # get the optimal alpha
        print("The alpha giving the best AUC is",alpha[ridge_score.index(np.max(ridge_score))])
```

```
The alpha giving the best AUC is 1.6
```



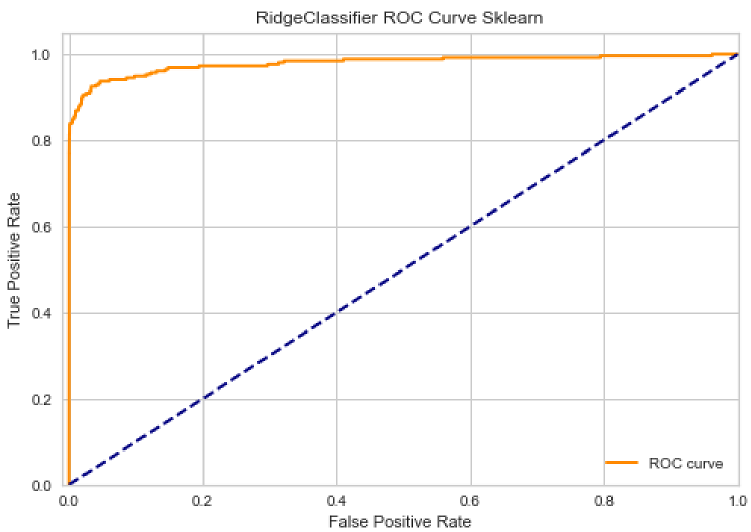
In [9]:
```python
# So we choose alpha=1.6
model_ridge =  RidgeClassifier(alpha=1.6, solver='saga').fit(Xtrain, Ytrain)
print('Validation score from RidgeClassifier: ', model_ridge.score(Xval,Yval))
```

```
Validation score from RidgeClassifier:  0.9988764439450862
```

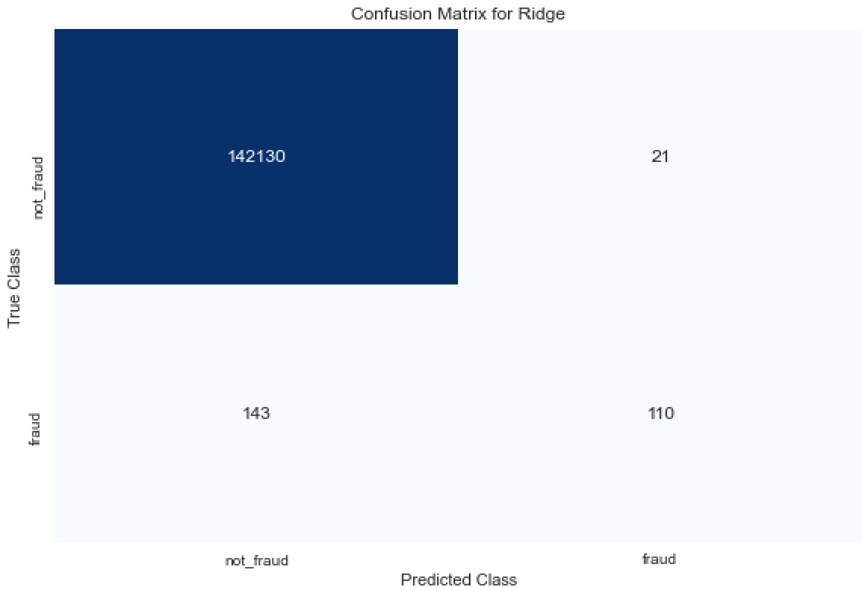
In [10]:
```python
# for testing sample
score_ridge = model_ridge.decision_function(Xtest)
Ypred_ridge = model_ridge.predict(Xtest)
```

In [11]:
```python
#AUC CURVE
fpr, tpr, thresholds = roc_curve(Ytest, score_ridge)
auc_ridge = auc(fpr, tpr)
print('RidgeClassifier Model AUC for testing set: {}'.format(auc_ridge))

plt.figure()
lw = 2
plt.plot(fpr, tpr, color='darkorange',
         lw=lw, label='ROC curve')
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([-0.01, 1.0])
plt.ylim([0.0, 1.05])

plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('RidgeClassifier ROC Curve Sklearn')
plt.legend(loc="lower right")
plt.show()
```

```
RidgeClassifier Model AUC for testing set: 0.9790540054509203
```



In [12]:
```
# precision and recall, confusion matrics
class_names = ['not_fraud', 'fraud']
matrix_ridge = confusion_matrix(Ytest, Ypred_ridge)
dataframe = pd.DataFrame(matrix_ridge, index=class_names, columns=class_names)

# Create heatmap
sns.heatmap(dataframe, annot=True, cbar=None, cmap="Blues", fmt = 'g')
plt.title("Confusion Matrix for Ridge"), plt.tight_layout()
plt.ylabel("True Class"), plt.xlabel("Predicted Class")
plt.show()
```



In [13]:
```
print('We have detected ' + str(matrix_ridge[1][1]) + ' frauds / ' +
      str(matrix_ridge[1][1]+matrix_ridge[1][0]) + ' total frauds.')
print('\nSo, the probability to detect a fraud is ' +
      str(matrix_ridge[1][1]/(matrix_ridge[1][1]+matrix_ridge[1][0])))
print("the accuracy is : "+ str((matrix_ridge[0][0] + matrix_ridge[1][1]) /
                                (sum(matrix_ridge[0]) + sum(matrix_ridge[1]))))
```

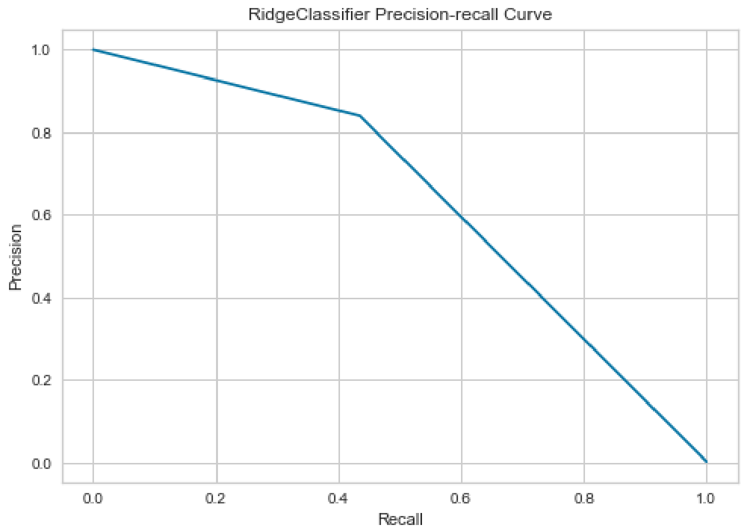
```
We have detected 110 frauds / 253 total frauds.

So, the probability to detect a fraud is 0.43478260869565216
the accuracy is : 0.9988483469565461
```

In [14]:
```
print(classification_report(Ytest, Ypred_ridge))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00    142151
           1       0.84      0.43      0.57       253

    accuracy                           1.00    142404
   macro avg       0.92      0.72      0.79    142404
weighted avg       1.00      1.00      1.00    142404
```

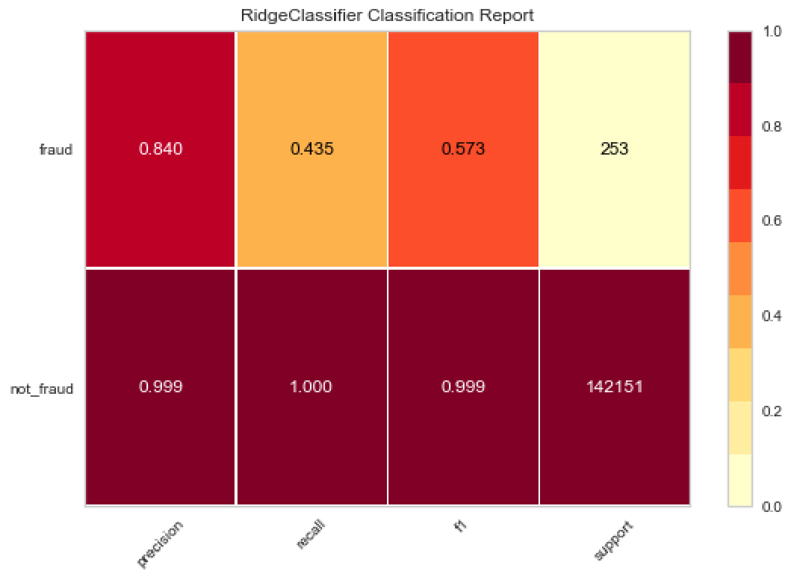
In [15]:

```python
precision, recall, _ = precision_recall_curve(Ytest, Ypred_ridge)
plt.plot(recall, precision)

plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("RidgeClassifier Precision-recall Curve")
plt.show()
```



In [16]:

```python
visualizer_ridge = ClassificationReport(model_ridge, classes = class_names,
                                        support = True)
visualizer_ridge.fit( Xtrain, Ytrain)        # Fit the visualizer and the model
visualizer_ridge.score(Xtest, Ytest)        # Evaluate the model on the test data
visualizer_ridge.show()
```




```
<matplotlib.axes._subplots.AxesSubplot at 0x1a218a35dc0>
```

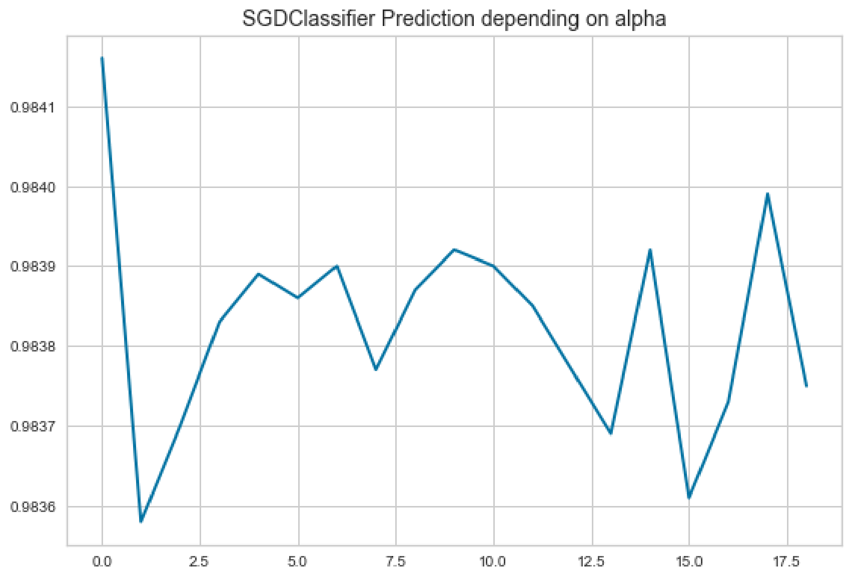
In [17]:
```
# evaluation
# calculate average error and standard deviation
testYDiff_ridge = np.abs(Ytest-Ypred_ridge)
avgErr_ridge = np.mean(testYDiff_ridge)
stdErr_ridge = np.std(testYDiff_ridge)

print('RidgeClassifier average error: {} ({})'.format(avgErr_ridge, stdErr_ridge))
```

```
RidgeClassifier average error: 0.0011516530434538355 (0.03391646707310977)
```

1.2 SGDClassifier(Regularized Linear)

In [18]:
```
# regularized linear models with stochastic gradient descent (SGD)
# loss = "log" == logistic so not choosing it
########SGDClassifier using the sklearn, finding the best learning rate #######
alpha = np.arange(0.001, 0.02, 0.001)
sgd_score = []

for num in alpha:
    model_sgd = SGDClassifier(alpha = num, max_iter=10000).fit(Xtrain,Ytrain)
    score_val = model_sgd.decision_function(Xval)
    fpr, tpr, thresholds = roc_curve(Yval, score_val)
    sgd_score.append(np.around(auc(fpr, tpr),5))

# plot the AUC graph
plt.plot(sgd_score,lw=2)
plt.title("SGDClassifier Prediction depending on alpha", size = 14)
plt.tight_layout()

# get the optimal alpha
print("The alpha giving the best AUC is", alpha[sgd_score.index(np.max(sgd_score))])
```

```
The alpha giving the best AUC is 0.001
```



In [19]:
```
#from above plot, we can say that the best alpha it gives us is 0.001.
model_sgd =  SGDClassifier(alpha = 0.001, max_iter=10000).fit(Xtrain,Ytrain)
print('Validation score from SGDClassifier: ', model_sgd.score(Xval,Yval))
```

```
Validation score from SGDClassifier:  0.9989466661985184
```

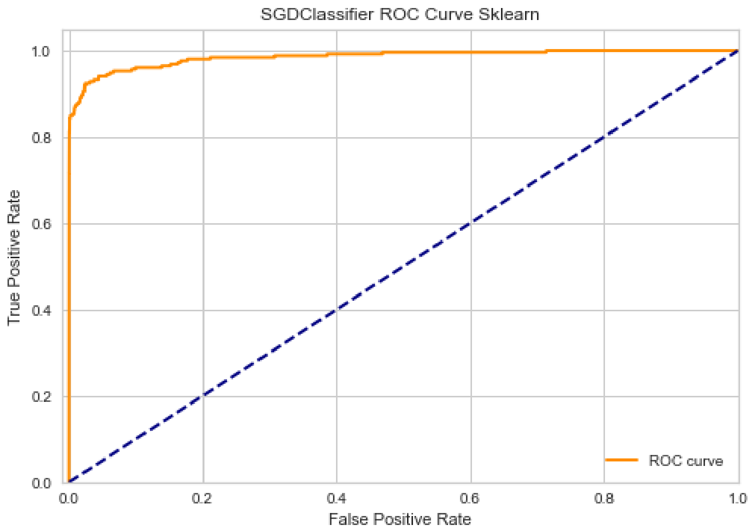
In [20]:

```python
# Prediction on test data
score_sgd = model_sgd.decision_function(Xtest)
Ypred_sgd = model_sgd.predict(Xtest)
```

In [21]:

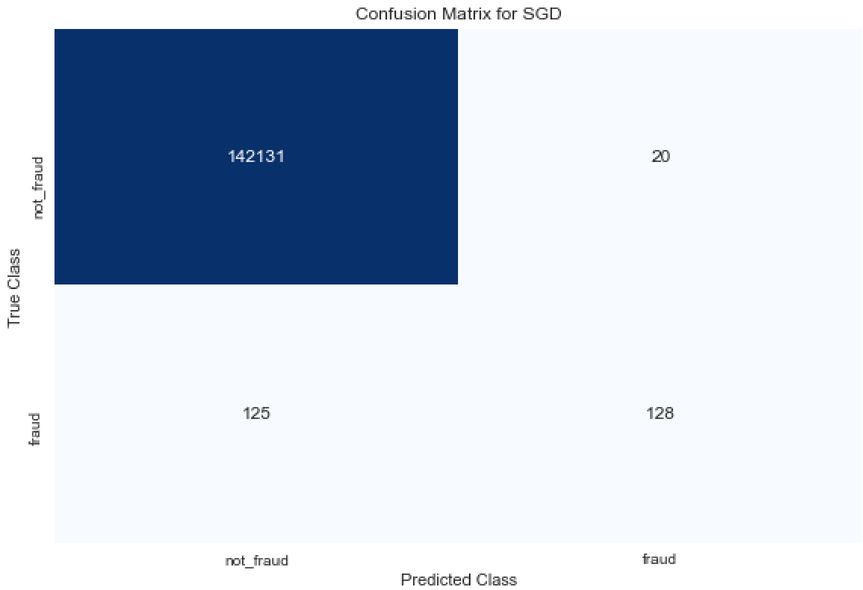
```python
#AUC CURVE
fpr, tpr, thresholds = roc_curve(Ytest, score_sgd)
auc_sgd = auc(fpr, tpr)
print('SGDClassifier Model AUC for testing set: {}'.format(auc_sgd))

plt.figure()
lw = 2
plt.plot(fpr, tpr, color='darkorange',
         lw=lw, label='ROC curve')
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([-0.01, 1.0])
plt.ylim([0.0, 1.05])

plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('SGDClassifier ROC Curve Sklearn')
plt.legend(loc="lower right")
plt.show()
```

```
SGDClassifier Model AUC for testing set: 0.9851334672980241
```



In [22]:

```python
# precision and recall, confusion matrics
class_names = ['not_fraud', 'fraud']
matrix_sgd = confusion_matrix(Ytest, Ypred_sgd)
dataframe = pd.DataFrame(matrix_sgd, index=class_names, columns=class_names)

# Create heatmap
sns.heatmap(dataframe, annot=True, cbar=None, cmap="Blues", fmt = 'g')
plt.title("Confusion Matrix for SGD"), plt.tight_layout()
plt.ylabel("True Class"), plt.xlabel("Predicted Class")
plt.show()
```



In [23]:

```python
print('We have detected ' + str(matrix_sgd[1][1]) + ' frauds / ' +
      str(matrix_sgd[1][1]+matrix_sgd[1][0]) + ' total frauds.')
print('\nSo, the probability to detect a fraud is ' +
      str(matrix_sgd[1][1]/(matrix_sgd[1][1]+matrix_sgd[1][0])))
print("the accuracy is : "+ str((matrix_sgd[0][0] + matrix_sgd[1][1]) /
                                (sum(matrix_sgd[0]) + sum(matrix_sgd[1]))))
```

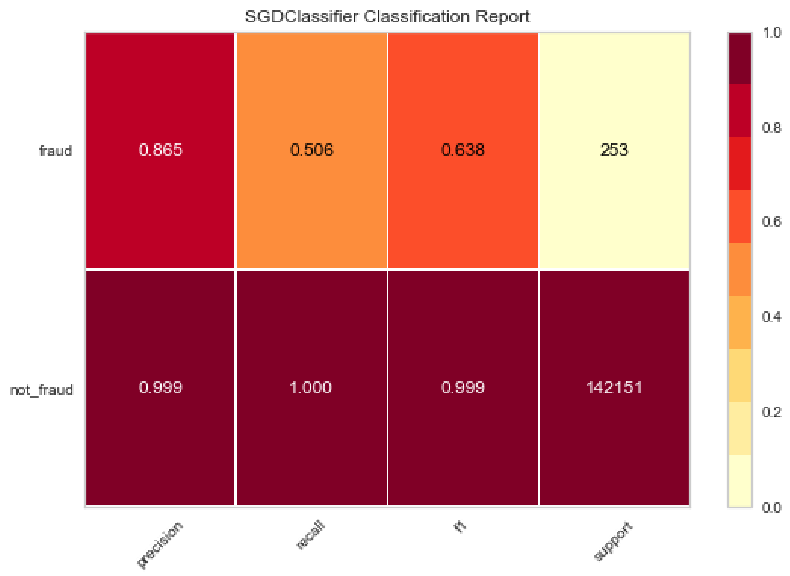
```
We have detected 128 frauds / 253 total frauds.

So, the probability to detect a fraud is 0.5059288537549407
the accuracy is : 0.9989817701749951
```

In [24]:

```python
print(classification_report(Ytest, Ypred_sgd))
```

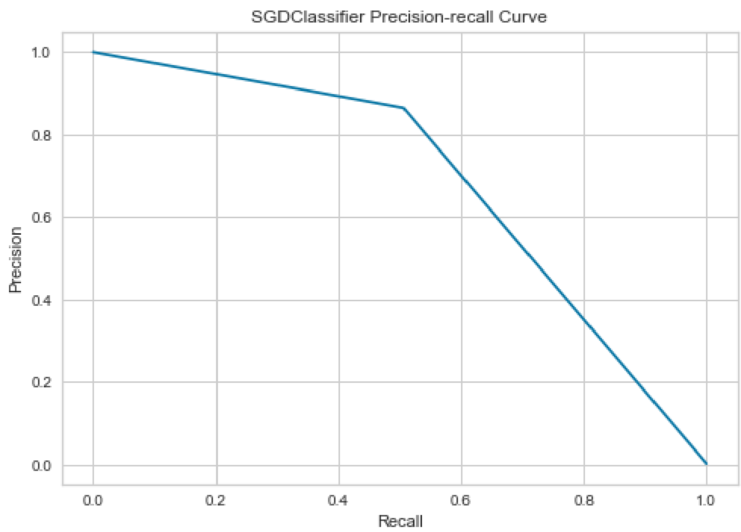
```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00    142151
           1       0.86      0.51      0.64       253

    accuracy                           1.00    142404
   macro avg       0.93      0.75      0.82    142404
weighted avg       1.00      1.00      1.00    142404
```

In [25]:
```
visualizer_sgd = ClassificationReport(model_sgd, classes = class_names,
                                      support = True)
visualizer_sgd.fit( Xtrain, Ytrain)        # Fit the visualizer and the model
visualizer_sgd.score(Xtest, Ytest)        # Evaluate the model on the test data
visualizer_sgd.show()
```




```
<matplotlib.axes._subplots.AxesSubplot at 0x1a21fcfbee0>
```

In [26]:
```
precision, recall, _ = precision_recall_curve(Ytest, Ypred_sgd)
plt.plot(recall, precision)

plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("SGDClassifier Precision-recall Curve")
plt.show()
```



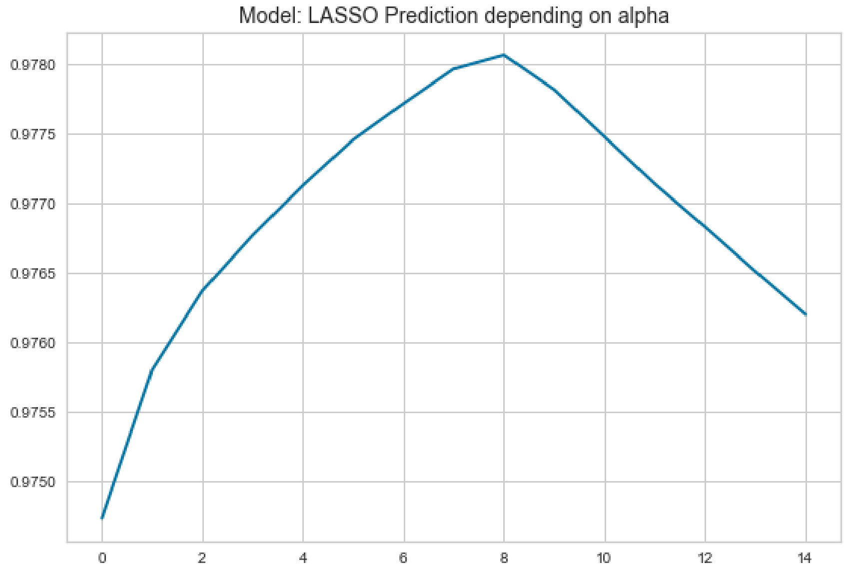
In [27]:
```python
# evaluation
# calculate average error and standard deviation
testYDiff_sgd = np.abs(Ytest-Ypred_sgd)
avgErr_sgd = np.mean(testYDiff_sgd)
stdErr_sgd = np.std(testYDiff_sgd)

print('SGDClassifier average error: {} ({})'.format(avgErr_sgd, stdErr_sgd))
```

```
SGDClassifier average error: 0.0010182298250049156 (0.03189346379790671)
```

1.3 LASSO

In [28]:
```python
########ElasticNet using the sklearn, finding the best learning rate #######
alpha = np.arange(0.0005, 0.002, 0.0001)
lasso_score = []

for a in alpha:
    model_lasso = ElasticNet(l1_ratio = 1,alpha = a,
                             max_iter=10000).fit(Xtrain, Ytrain)
    score_val = model_lasso.predict(Xval) # it gives probability
    fpr, tpr, thresholds = roc_curve(Yval, score_val)
    lasso_score.append(np.around(auc(fpr, tpr),5))

# plot the AUC graph
plt.plot(lasso_score,lw=2)
plt.title("Model: LASSO Prediction depending on alpha", size = 14)
plt.tight_layout()

# get the optimal alpha
print("The alpha giving the best AUC is",alpha[lasso_score.index(np.max(lasso_score))])
```

```
The alpha giving the best AUC is 0.0013000000000000004
```



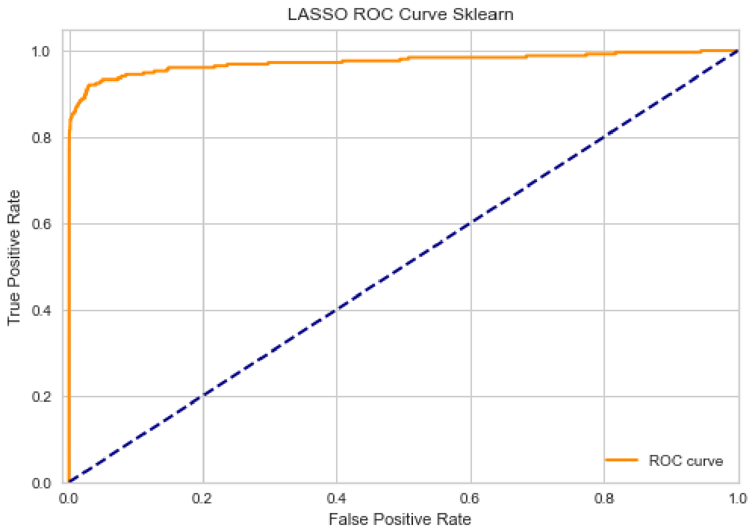
In [29]:
```python
#from above plot, we can say that the best alpha it gives us is 0.0013.
model_lasso = ElasticNet(l1_ratio=1,alpha=0.0013,max_iter=10000).fit(Xtrain, Ytrain)
print('Validation score from LASSO: ', model_lasso.score(Xval,Yval))
```

```
Validation score from LASSO:  0.5090500728746152
```

In [30]:
```python
# Prediction on test data
score_lasso = model_lasso.predict(Xtest)
Ypred_lasso = [round(i) for i in score_lasso]
```

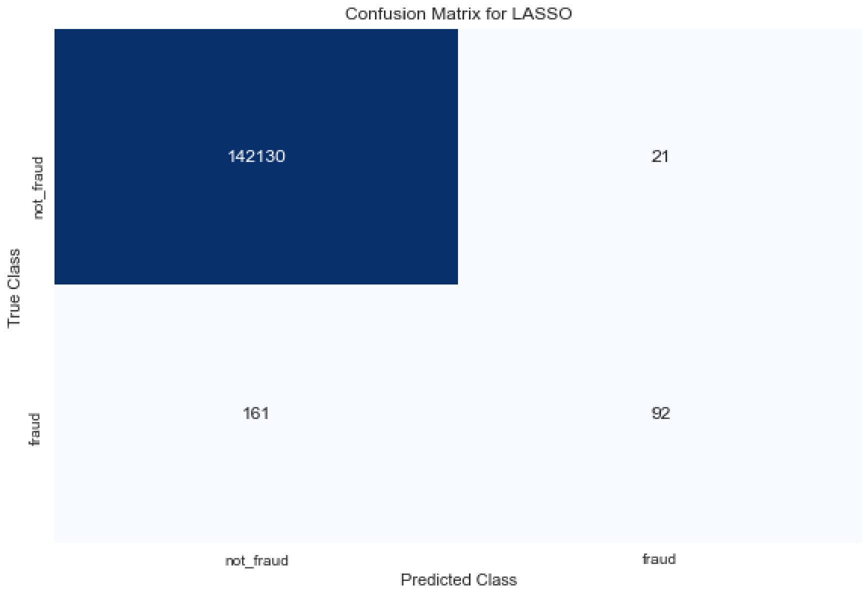
In [31]:
```python
#AUC CURVE
fpr, tpr, thresholds = roc_curve(Ytest, score_lasso)
auc_lasso = auc(fpr, tpr)
print('LASSO Model AUC for testing set: {}'.format(auc_lasso))

plt.figure()
lw = 2
plt.plot(fpr, tpr, color='darkorange',
         lw=lw, label='ROC curve')
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([-0.01, 1.0])
plt.ylim([0.0, 1.05])

plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('LASSO ROC Curve Sklearn')
plt.legend(loc="lower right")
plt.show()
```

```
LASSO Model AUC for testing set: 0.9736452939051645
```



In [32]:

```
# precision and recall, confusion matrics
class_names = ['not_fraud', 'fraud']
matrix_lasso = confusion_matrix(Ytest, Ypred_lasso)
dataframe = pd.DataFrame(matrix_lasso, index=class_names, columns=class_names)

# Create heatmap
sns.heatmap(dataframe, annot=True, cbar=None, cmap="Blues", fmt = 'g')
plt.title("Confusion Matrix for LASSO"), plt.tight_layout()
plt.ylabel("True Class"), plt.xlabel("Predicted Class")
plt.show()
```



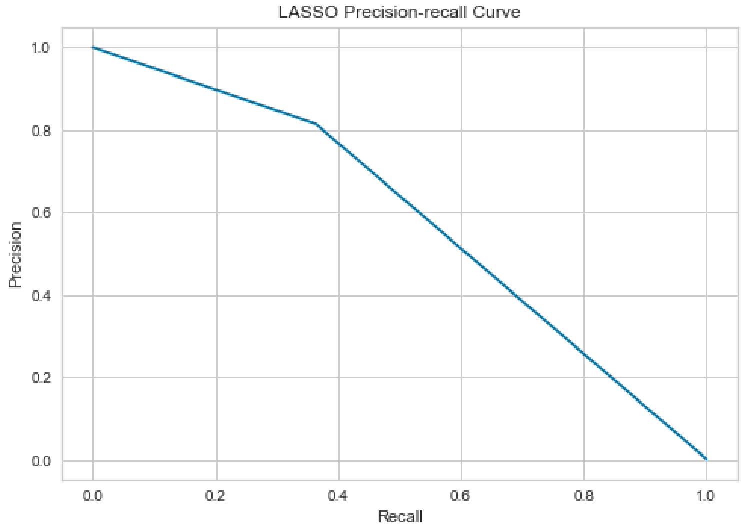
In [33]:

```
print('We have detected ' + str(matrix_lasso[1][1]) + ' frauds / ' +
      str(matrix_lasso[1][1]+matrix_lasso[1][0]) + ' total frauds.')
print('\nSo, the probability to detect a fraud is ' +
      str(matrix_lasso[1][1]/(matrix_lasso[1][1]+matrix_lasso[1][0])))
print("the accuracy is : "+ str((matrix_lasso[0][0] + matrix_lasso[1][1]) /
                                (sum(matrix_lasso[0]) + sum(matrix_lasso[1]))))
```

```
We have detected 92 frauds / 253 total frauds.

So, the probability to detect a fraud is 0.36363636363636365
the accuracy is : 0.9987219460127524
```

In [34]:

```
precision, recall, _ = precision_recall_curve(Ytest, Ypred_lasso)
plt.plot(recall, precision)

plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("LASSO Precision-recall Curve")
plt.show()
```



In [35]:

```
print(classification_report(Ytest, Ypred_lasso))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00    142151
           1       0.81      0.36      0.50       253

    accuracy                           1.00    142404
   macro avg       0.91      0.68      0.75    142404
weighted avg       1.00      1.00      1.00    142404
```

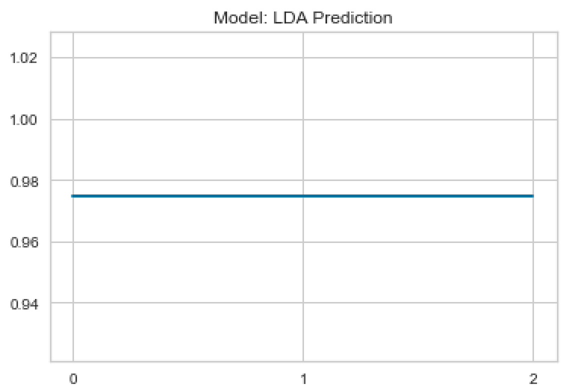
In [36]:

```
# evaluation
# calculate average error and standard deviation
testYDiff_lasso = np.abs(Ytest-Ypred_lasso)
avgErr_lasso = np.mean(testYDiff_lasso)
stdErr_lasso = np.std(testYDiff_lasso)

print('LASSO average error: {} ({})'.format(avgErr_lasso, stdErr_lasso))
```

```
LASSO average error: 0.0012780539872475493 (0.03572702849738878)
```

1.4 Linear Discriminant Analysis

In [39]:
```
##################using the sklearn model, finding the best solver################
solvers = ['svd', 'lsqr', 'eigen']
lda_score = []

for sol in solvers:
    model_lda = LinearDiscriminantAnalysis(solver=sol).fit(Xtrain, Ytrain)
    score_val = model_lda.predict_proba(Xval)[:,1]
    fpr, tpr, thresholds = roc_curve(Yval, score_val)
    lda_score.append(np.around(auc(fpr, tpr),5))

# plot the AUC graph
plt.plot(lda_score,lw=2)
x_major_locator=MultipleLocator(1)
ax=plt.gca()
ax.xaxis.set_major_locator(x_major_locator)
plt.title("Model: LDA Prediction")
plt.show()

# get the optimal alpha
print("The solver giving the best AUC is",solvers[lda_score.index(np.max(lda_score))])
```




```
The solver giving the best AUC is svd
```

In [40]:
```
#from above plot, we just choose the most common one "svd".
model_lda = LinearDiscriminantAnalysis(solver='svd').fit(Xtrain, Ytrain)
print('Validation score from LDA: ', model_lda.score(Xval,Yval))
```

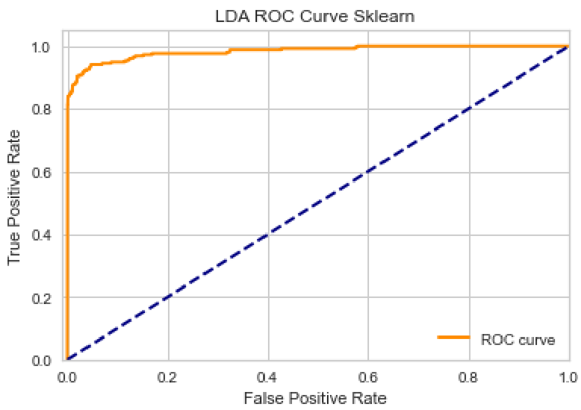
```
Validation score from LDA:  0.9994382219725431
```

In [41]:
```
# Prediction on test data
score_lda = model_lda.predict_proba(Xtest)[:,1]
Ypred_lda = model_lda.predict(Xtest)
```

In [48]:

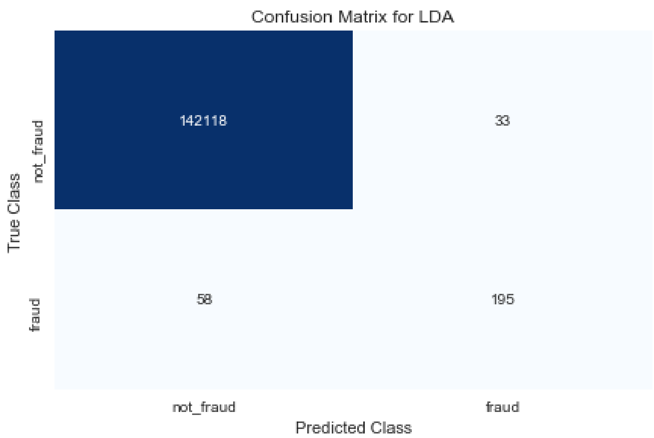
```
#AUC CURVE
fpr, tpr, thresholds = roc_curve(Ytest, score_lda)
auc_lda = auc(fpr, tpr)
print('LDA Model AUC for testing set: {}'.format(auc_lda))

plt.figure()
lw = 2
plt.plot(fpr, tpr, color='darkorange',
         lw=lw, label='ROC curve')
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([-0.01, 1.0])
plt.ylim([0.0, 1.05])

plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('LDA ROC Curve Sklearn')
plt.legend(loc="lower right")
plt.show()
```

```
LDA Model AUC for testing set: 0.983246646672526
```



In [43]:

```
# precision and recall, confusion matrics
class_names = ['not_fraud', 'fraud']
matrix_lda = confusion_matrix(Ytest, Ypred_lda)
dataframe = pd.DataFrame(matrix_lda, index=class_names, columns=class_names)

# Create heatmap
sns.heatmap(dataframe, annot=True, cbar=None, cmap="Blues", fmt = 'g')
plt.title("Confusion Matrix for LDA"), plt.tight_layout()
plt.ylabel("True Class"), plt.xlabel("Predicted Class")
plt.show()
```



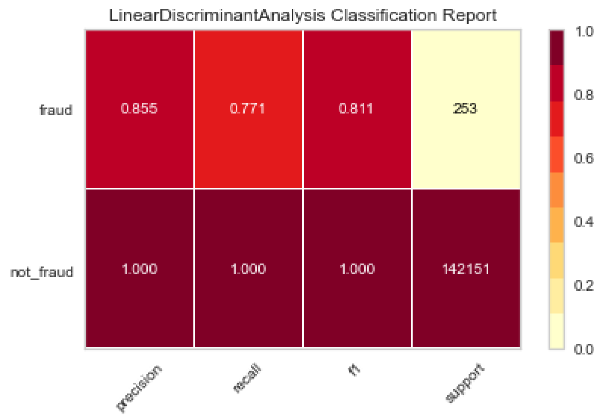
In [44]:
```
print('We have detected ' + str(matrix_lda[1][1]) + ' frauds / ' +
      str(matrix_lda[1][1]+matrix_lda[1][0]) + ' total frauds.')
print('\nSo, the probability to detect a fraud is ' +
      str(matrix_lda[1][1]/(matrix_lda[1][1]+matrix_lda[1][0])))
print("the accuracy is : "+ str((matrix_lda[0][0] + matrix_lda[1][1]) /
                                (sum(matrix_lda[0]) + sum(matrix_lda[1]))))
```

```
We have detected 195 frauds / 253 total frauds.

So, the probability to detect a fraud is 0.7707509881422925
the accuracy is : 0.9993609730063763
```

In [45]:
```
print(classification_report(Ytest, Ypred_lda))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00    142151
           1       0.86      0.77      0.81       253

    accuracy                           1.00    142404
   macro avg       0.93      0.89      0.91    142404
weighted avg       1.00      1.00      1.00    142404
```

In [46]:
```
visualizer_lda = ClassificationReport(model_lda, classes = class_names,
                                      support = True)
visualizer_lda.fit( Xtrain, Ytrain)        # Fit the visualizer and the model
visualizer_lda.score(Xtest, Ytest)        # Evaluate the model on the test data
visualizer_lda.show()
```




```
<matplotlib.axes._subplots.AxesSubplot at 0x1a218ff7ac0>
```

In [47]:
```
# evaluation
# calculate average error and standard deviation
testYDiff_lda = np.abs(Ytest-Ypred_lda)
avgErr_lda = np.mean(testYDiff_lda)
stdErr_lda = np.std(testYDiff_lda)

print('LASSO average error: {} ({})'.format(avgErr_lda, stdErr_lda))
```

```
LASSO average error: 0.0006390269936237746 (0.025270904972422226)
```

Finding Best Linear Classification Model

AUC Score

In [49]:
```
auc_linear = pd.DataFrame({
    'Model': ['RidgeClassifier', 'SGDClassifier', 'LASSO','LDA'],
    'AUC Score': [auc_ridge, auc_sgd, auc_lasso, auc_lda]})

auc_linear.sort_values(by='AUC Score', ascending=False)
```

	Model	AUC Score
1	SGDClassifier	0.985133
3	LDA	0.983247
0	RidgeClassifier	0.979054
2	LASSO	0.973645

Precision

In [50]:
```
precision_ridge = matrix_ridge[1][1]/(matrix_ridge[1][1]+matrix_ridge[0][1])
precision_sgd = matrix_sgd[1][1]/(matrix_sgd[1][1]+matrix_sgd[0][1])
precision_lasso = matrix_lasso[1][1]/(matrix_lasso[1][1]+matrix_lasso[0][1])
precision_lda = matrix_lda[1][1]/(matrix_lda[1][1]+matrix_lda[0][1])

precision_linear = pd.DataFrame({
    'Model': ['RidgeClassifier', 'SGDClassifier', 'LASSO', 'LDA'],
    'Precision': [precision_ridge, precision_sgd, precision_lasso, precision_lda]})

precision_linear.sort_values(by='Precision', ascending=False)
```

	Model	Precision
1	SGDClassifier	0.864865
3	LDA	0.855263
0	RidgeClassifier	0.839695
2	LASSO	0.814159

Recall

In [51]:
```
recall_ridge = matrix_ridge[1][1]/(matrix_ridge[1][1]+matrix_ridge[1][0])
recall_sgd = matrix_sgd[1][1]/(matrix_sgd[1][1]+matrix_sgd[1][0])
recall_lasso = matrix_lasso[1][1]/(matrix_lasso[1][1]+matrix_lasso[1][0])
recall_lda = matrix_lda[1][1]/(matrix_lda[1][1]+matrix_lda[1][0])

recall_linear = pd.DataFrame({
    'Model': ['RidgeClassifier', 'SGDClassifier', 'LASSO','LDA'],
    'Recall': [recall_ridge, recall_sgd, recall_lasso,recall_lda]})

recall_linear.sort_values(by='Recall', ascending=False)
```

	Model	Recall
3	LDA	0.770751
1	SGDClassifier	0.505929
0	RidgeClassifier	0.434783
2	LASSO	0.363636

Conclusion---Best linear Model

So we would think that **LinearDiscriminantAnalysis** is the best among these three linear models.

In [52]:
```python
acc_lda = (matrix_lda[0][0] + matrix_lda[1][1])/(sum(matrix_lda[0])+sum(matrix_lda[1]))

linear_model = pd.DataFrame({
    'Model': ['LinearDiscriminantAnalysis'],
    'AUC Score': [auc_lda],
    'Recall': [recall_lda],
    'Precision': [precision_lda],
    'Accuracy': [acc_lda]
})

display(linear_model)
```

	Model	AUC Score	Recall	Precision	Accuracy
0	LinearDiscriminantAnalysis	0.983247	0.770751	0.855263	0.999361

2. Logistic Regression

2.1 Simple Logistic Regression

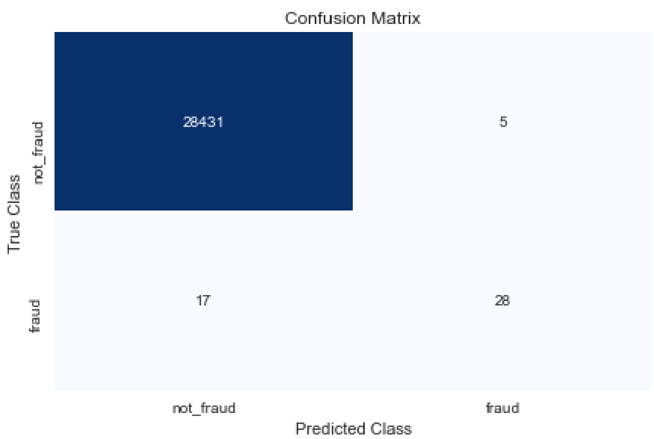
In [46]:
```python
###############Logistic regression using the sklearn ###################
model = LogisticRegression()
model.fit(Xtrain, Ytrain)
print('Validation score: ', model.score(Xval,Yval))
```

```
Validation score:  0.9992275552122467
```

In [47]:
```python
prediction = model.predict(Xval)
r2_score(Yval, prediction)
```

```
0.5103374439286664
```

In [48]:
```python
class_names = ['not_fraud', 'fraud']
matrix = confusion_matrix(Yval, prediction)
# Create pandas dataframe
dataframe = pd.DataFrame(matrix, index=class_names, columns=class_names)
# Create heatmap
sns.heatmap(dataframe, annot=True, cbar=None, cmap="Blues", fmt = 'g')
plt.title("Confusion Matrix"), plt.tight_layout()
plt.ylabel("True Class"), plt.xlabel("Predicted Class")
plt.show()
```



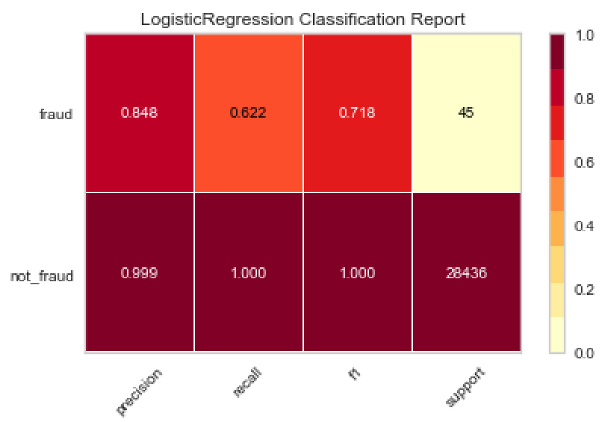
In [49]:
```
print('We have detected ' + str(matrix[1][1]) + ' frauds / ' +
      str(matrix[1][1]+matrix[1][0]) + ' total frauds.')
print('\nSo, the probability to detect a fraud is ' +
      str(matrix[1][1]/(matrix[1][1]+matrix[1][0])))
print("the accuracy is : "+ str((matrix[0][0]+matrix[1][1]) /
                                (sum(matrix[0]) + sum(matrix[1]))))
```

```
We have detected 28 frauds / 45 total frauds.

So, the probability to detect a fraud is 0.6222222222222222
the accuracy is : 0.9992275552122467
```

In [51]:
```
print(classification_report(Yval, prediction))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     28436
           1       0.85      0.62      0.72        45

    accuracy                           1.00     28481
   macro avg       0.92      0.81      0.86     28481
weighted avg       1.00      1.00      1.00     28481
```

In [52]:
```
visualizer = ClassificationReport(model, classes = class_names, support = True)
visualizer.fit( Xtrain, Ytrain)        # Fit the visualizer and the model
visualizer.score(Xval, Yval)        # Evaluate the model on the test data
visualizer.show()
```




```
<matplotlib.axes._subplots.AxesSubplot at 0x1d9a49ccdf0>
```

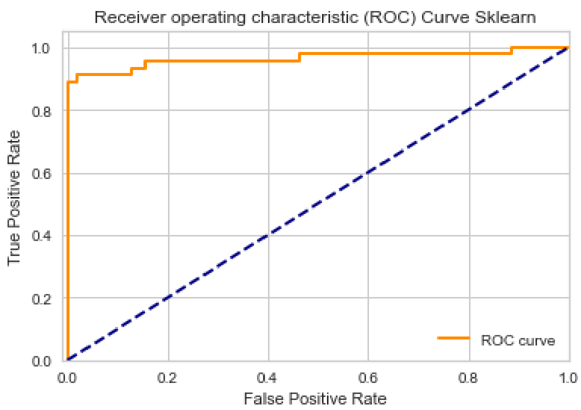
In [53]:
```
# evaluation
# calculate average error and standard deviation
testYDiff = np.abs(Yval-prediction)
avgErr = np.mean(testYDiff)
stdErr = np.std(testYDiff)

print('Logistic regression average error: {} ({})'.format(avgErr, stdErr))
```

```
Logistic regression average error: 0.000772444787753239 (0.027782154646519258)
```

In [54]:

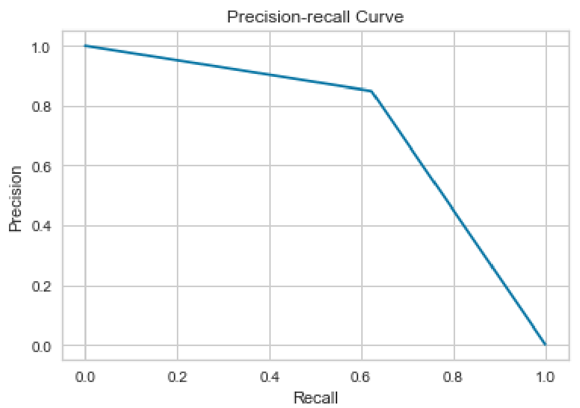
```
#AUC CURVE
fpr2, tpr2, thresholds = roc_curve(Yval, model.predict_proba(Xval)[:,1])
print('Logistic Regression AUC: {}'.format(auc(fpr2, tpr2)))

plt.figure()
lw = 2
plt.plot(fpr2, tpr2, color='darkorange',
         lw=lw, label='ROC curve')
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([-0.01, 1.0])
plt.ylim([0.0, 1.05])

plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic (ROC) Curve Sklearn')
plt.legend(loc="lower right")
plt.show()
```

```
Logistic Regression AUC: 0.9631390569075193
```



In [55]:

```
precision, recall, _ = precision_recall_curve(Yval, model.predict(Xval))
plt.plot(recall, precision)

plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("Precision-recall Curve")
plt.show()
```



2.2 Logistic regression -- with Ridge Penalization, solver = "sag"

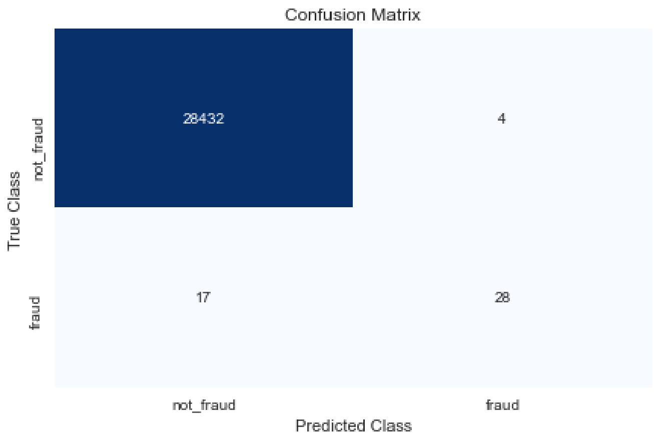
In [57]:
```
###############Logistic regression -- with Ridge Penalization ###################
##regression with L2 regularization
model_ridge = LogisticRegression(penalty = "l2",solver = "sag")
model_ridge.fit(Xtrain, Ytrain)
print('Validation score: ', model_ridge.score(Xval,Yval))
```

```
Validation score:  0.9992626663389628
```

In [58]:
```
prediction_ridge = model_ridge.predict(Xval)
r2_score(Yval, prediction_ridge)
```

```
0.5325948328409997
```

In [59]:
```
class_names = ['not_fraud', 'fraud']
matrix = confusion_matrix(Yval, prediction_ridge)
# Create pandas dataframe
dataframe = pd.DataFrame(matrix, index=class_names, columns=class_names)
# Create heatmap
sns.heatmap(dataframe, annot=True, cbar=None, cmap="Blues", fmt = 'g')
plt.title("Confusion Matrix"), plt.tight_layout()
plt.ylabel("True Class"), plt.xlabel("Predicted Class")
plt.show()
```



In [60]:
```
print('We have detected ' + str(matrix[1][1]) + ' frauds / ' +
      str(matrix[1][1]+matrix[1][0]) + ' total frauds.')
print('\nSo, the probability to detect a fraud is ' +
      str(matrix[1][1]/(matrix[1][1]+matrix[1][0])))
print("the accuracy is : "+str((matrix[0][0]+matrix[1][1]) /
                               (sum(matrix[0]) + sum(matrix[1]))))
```

```
We have detected 28 frauds / 45 total frauds.

So, the probability to detect a fraud is 0.6222222222222222
the accuracy is : 0.9992626663389628
```

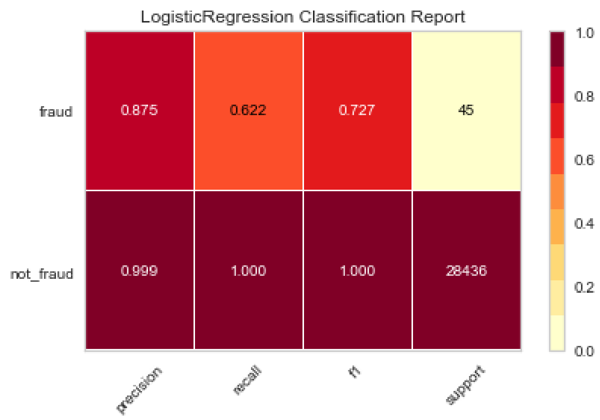
In [61]:

```python
print(classification_report(Yval, prediction_ridge))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     28436
           1       0.88      0.62      0.73        45

    accuracy                           1.00     28481
   macro avg       0.94      0.81      0.86     28481
weighted avg       1.00      1.00      1.00     28481
```

In [62]:

```python
visualizer = ClassificationReport(model_ridge, classes = class_names, support = True)
visualizer.fit( Xtrain, Ytrain)        # Fit the visualizer and the model
visualizer.score(Xval, Yval)        # Evaluate the model on the test data
visualizer.show()
```




```
<matplotlib.axes._subplots.AxesSubplot at 0x1d9acdedc70>
```

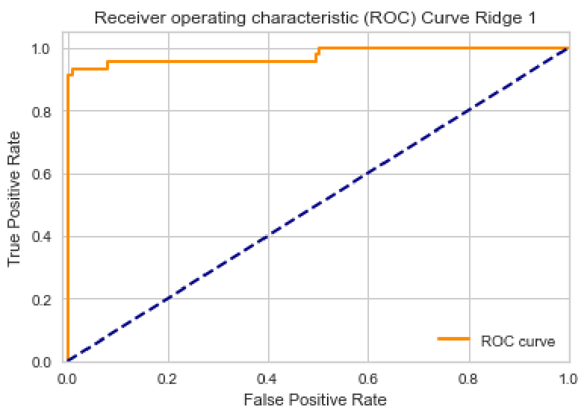
In [63]:

```python
# evaluation
# calculate average error and standard deviation
testYDiff = np.abs(Yval-prediction_ridge)
avgErr = np.mean(testYDiff)
stdErr = np.std(testYDiff)

print('Logistic regression average error: {} ({})'.format(avgErr, stdErr))
```

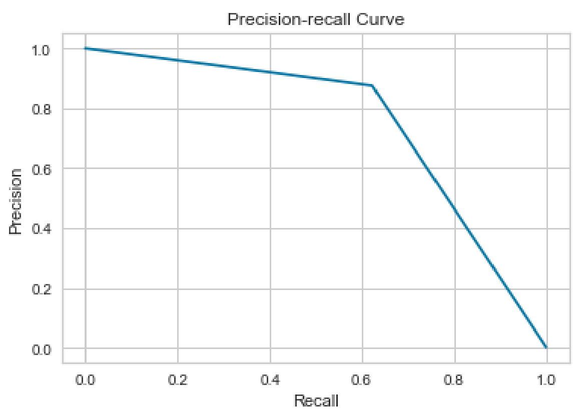
```
Logistic regression average error: 0.0007373336610371826 (0.027143875922746998)
```

In [64]:
```
#AUC CURVE
fpr2, tpr2, thresholds = roc_curve(Yval, model_ridge.predict_proba(Xval)[:,1])
print('Logistic Regression AUC: {}'.format(auc(fpr2, tpr2)))

plt.figure()
lw = 2
plt.plot(fpr2, tpr2, color='darkorange',
         lw=lw, label='ROC curve')
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([-0.01, 1.0])
plt.ylim([0.0, 1.05])

plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic (ROC) Curve Ridge 1')
plt.legend(loc="lower right")
plt.show()
```

```
Logistic Regression AUC: 0.975684187493162
```



In [65]:
```
precision, recall, _ = precision_recall_curve(Yval, model_ridge.predict(Xval))
plt.plot(recall, precision)

plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("Precision-recall Curve")
plt.show()
```



2.3 Logistic regression -- with Ridge Penalization, solver = "liblinear"

In [66]:

```
###############Logistic regression -- with Ridge Penalization ##################
#regression with L2 regularization
model_ridge2 = LogisticRegression(penalty = "l2",solver = "liblinear")
model_ridge2.fit(Xtrain, Ytrain)
print('Validation score: ', model_ridge2.score(Xval,Yval))
```

```
Validation score:  0.9991924440855307
```

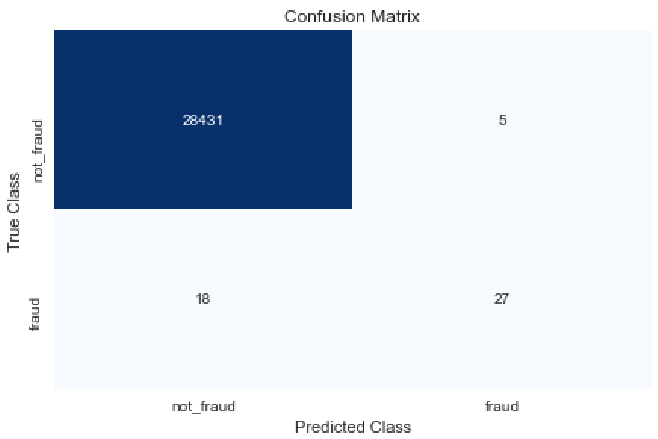
In [67]:

```
prediction_ridge2 = model_ridge2.predict(Xval)
r2_score(Yval, prediction_ridge2)
```

```
0.4880800550163331
```

In [68]:

```
class_names = ['not_fraud', 'fraud']
matrix = confusion_matrix(Yval, prediction_ridge2)
# Create pandas dataframe
dataframe = pd.DataFrame(matrix, index=class_names, columns=class_names)
# Create heatmap
sns.heatmap(dataframe, annot=True, cbar=None, cmap="Blues", fmt = 'g')
plt.title("Confusion Matrix"), plt.tight_layout()
plt.ylabel("True Class"), plt.xlabel("Predicted Class")
plt.show()
```



In [69]:

```
print('We have detected ' + str(matrix[1][1]) + ' frauds / ' +
      str(matrix[1][1]+matrix[1][0]) + ' total frauds.')
print('\nSo, the probability to detect a fraud is ' +
      str(matrix[1][1]/(matrix[1][1]+matrix[1][0])))
print("the accuracy is : "+str((matrix[0][0]+matrix[1][1]) /
                               (sum(matrix[0]) + sum(matrix[1]))))
```

```
We have detected 27 frauds / 45 total frauds.

So, the probability to detect a fraud is 0.6
the accuracy is : 0.9991924440855307
```

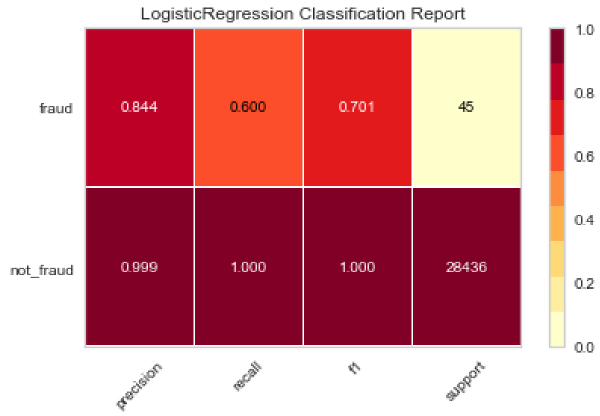
In [70]:

```
print(classification_report(Yval, prediction_ridge2))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     28436
           1       0.84      0.60      0.70        45

    accuracy                           1.00     28481
   macro avg       0.92      0.80      0.85     28481
weighted avg       1.00      1.00      1.00     28481
```

In [71]:

```
visualizer = ClassificationReport(model_ridge2, classes = class_names, support = True)
visualizer.fit( Xtrain, Ytrain)        # Fit the visualizer and the model
visualizer.score(Xval, Yval)        # Evaluate the model on the test data
visualizer.show()
```




```
<matplotlib.axes._subplots.AxesSubplot at 0x1d9ad727340>
```

In [72]:

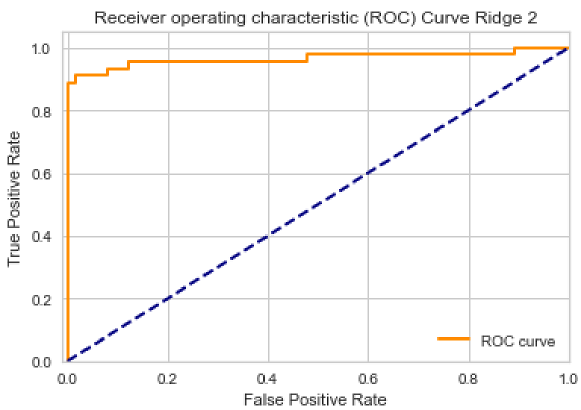
```
# evaluation
# calculate average error and standard deviation
testYDiff = np.abs(Yval-prediction_ridge2)
avgErr = np.mean(testYDiff)
stdErr = np.std(testYDiff)

print('Logistic regression average error: {} ({})'.format(avgErr, stdErr))
```

```
Logistic regression average error: 0.0008075559144692953 (0.02840605160725969)
```

In [73]:

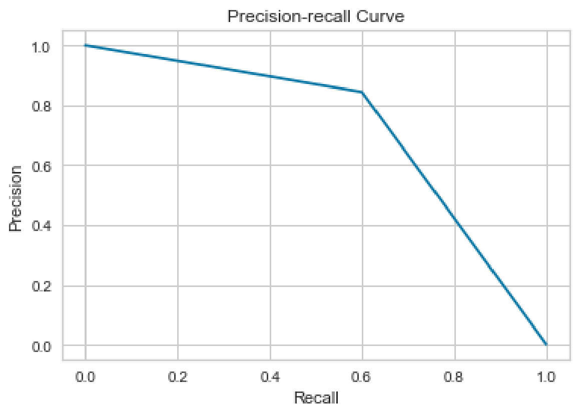
```
#AUC CURVE
fpr2, tpr2, thresholds = roc_curve(Yval, model_ridge2.predict_proba(Xval)[:,1])
print('Logistic Regression AUC: {}'.format(auc(fpr2, tpr2)))

plt.figure()
lw = 2
plt.plot(fpr2, tpr2, color='darkorange',
         lw=lw, label='ROC curve')
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([-0.01, 1.0])
plt.ylim([0.0, 1.05])

plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic (ROC) Curve Ridge 2')
plt.legend(loc="lower right")
plt.show()
```

```
Logistic Regression AUC: 0.9646137134461794
```



In [74]:

```
precision, recall, _ = precision_recall_curve(Yval, model_ridge2.predict(Xval))
plt.plot(recall, precision)

plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("Precision-recall Curve")
plt.show()
```



2.4 Logistic regression -- with Lasso Penalization, solver = "liblinear"

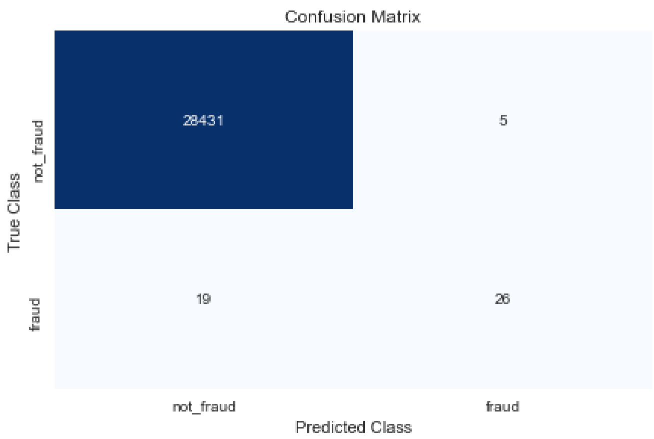
In [75]:
```
###############Logistic regression -- with Lasso Penalization ###################
#regression with L1 regularization
model_lasso = LogisticRegression(penalty = "l1",solver = "liblinear")
model_lasso.fit(Xtrain, Ytrain)
print('Validation score: ', model_lasso.score(Xval,Yval))
```

```
Validation score:  0.9991573329588147
```

In [76]:
```
prediction_lasso = model_lasso.predict(Xval)
r2_score(Yval, prediction_lasso)
```

```
0.4658226661039997
```

In [77]:
```
class_names = ['not_fraud', 'fraud']
matrix = confusion_matrix(Yval, prediction_lasso)
# Create pandas dataframe
dataframe = pd.DataFrame(matrix, index=class_names, columns=class_names)
# Create heatmap
sns.heatmap(dataframe, annot=True, cbar=None, cmap="Blues", fmt = 'g')
plt.title("Confusion Matrix"), plt.tight_layout()
plt.ylabel("True Class"), plt.xlabel("Predicted Class")
plt.show()
```



In [78]:
```
print('We have detected ' + str(matrix[1][1]) + ' frauds / ' + str(matrix[1][1]+matrix[1][0]) + '
 total frauds.')
print('\nSo, the probability to detect a fraud is ' + str(matrix[1][1]/(matrix[1][1]+matrix[1][0
])))
print("the accuracy is : "+str((matrix[0][0]+matrix[1][1]) / (sum(matrix[0]) + sum(matrix[1]))))
```

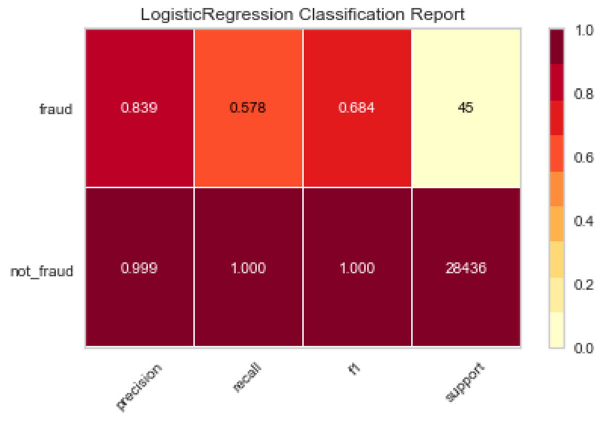
```
We have detected 26 frauds / 45 total frauds.

So, the probability to detect a fraud is 0.5777777777777777
the accuracy is : 0.9991573329588147
```

In [79]:
```
print(classification_report(Yval, prediction_lasso))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     28436
           1       0.84      0.58      0.68        45

    accuracy                           1.00     28481
   macro avg       0.92      0.79      0.84     28481
weighted avg       1.00      1.00      1.00     28481
```

In [80]:

```
visualizer = ClassificationReport(model_lasso, classes = class_names, support = True)
visualizer.fit( Xtrain, Ytrain)        # Fit the visualizer and the model
visualizer.score(Xval, Yval)        # Evaluate the model on the test data
visualizer.show()
```




```
<matplotlib.axes._subplots.AxesSubplot at 0x1d9acd95cd0>
```

In [81]:

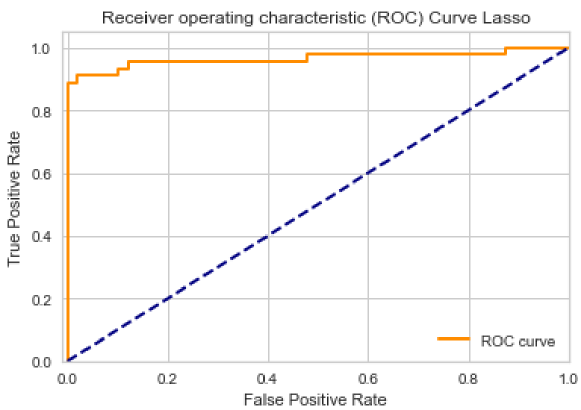
```
# evaluation
# calculate average error and standard deviation


testYDiff = np.abs(Yval-prediction_lasso)
avgErr = np.mean(testYDiff)
stdErr = np.std(testYDiff)

print('Logistic regression average error: {} ({})'.format(avgErr, stdErr))
```

```
Logistic regression average error: 0.0008426670411853516 (0.029016494506453595)
```

In [82]:

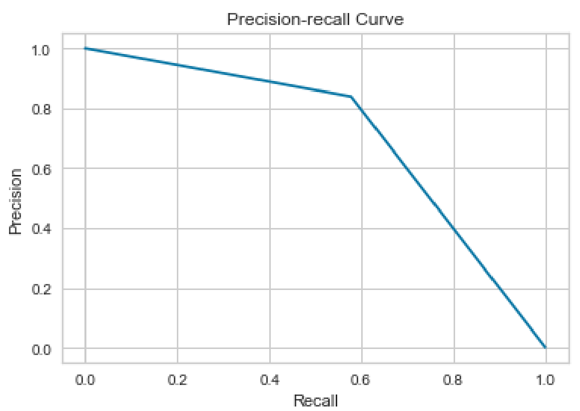
```
#AUC CURVE
fpr2, tpr2, thresholds = roc_curve(Yval, model_lasso.predict_proba(Xval)[:,1])
print('Logistic Regression AUC: {}'.format(auc(fpr2, tpr2)))

plt.figure()
lw = 2
plt.plot(fpr2, tpr2, color='darkorange',
         lw=lw, label='ROC curve')
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([-0.01, 1.0])
plt.ylim([0.0, 1.05])

plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic (ROC) Curve Lasso')
plt.legend(loc="lower right")
plt.show()
```

```
Logistic Regression AUC: 0.9643706725434114
```



In [84]:

```
precision, recall, _ = precision_recall_curve(Yval, model_lasso.predict(Xval))
plt.plot(recall, precision)

plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("Precision-recall Curve")
plt.show()
```



2.5 Logistic regression -- with Lasso Penalization, solver = "saga"

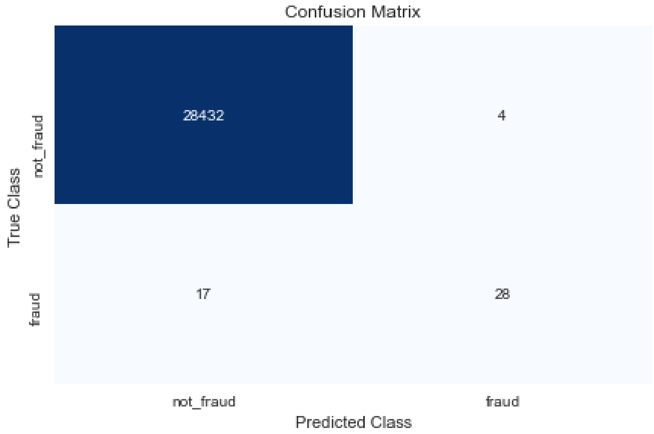
In [85]:
```
###############Logistic regression -- with Lasso Penalization ###################
#regression with L1 regularization
model_lasso2 = LogisticRegression(penalty = "l1",solver = "saga")
model_lasso2.fit(Xtrain, Ytrain)
print('Validation score: ', model_lasso2.score(Xval,Yval))
```

```
Validation score:  0.9992626663389628
```

In [86]:
```
prediction_lasso2 = model_lasso2.predict(Xval)
r2_score(Yval, prediction_lasso2)
```

```
0.5325948328409997
```

In [87]:
```
prediction_lasso2 = model_lasso2.predict(Xval)

class_names = ['not_fraud', 'fraud']
matrix = confusion_matrix(Yval, prediction_lasso2)
# Create pandas dataframe
dataframe = pd.DataFrame(matrix, index=class_names, columns=class_names)

# Create heatmap
sns.heatmap(dataframe, annot=True, cbar=None, cmap="Blues", fmt = 'g')
plt.title("Confusion Matrix"), plt.tight_layout()
plt.ylabel("True Class"), plt.xlabel("Predicted Class")
plt.show()
```



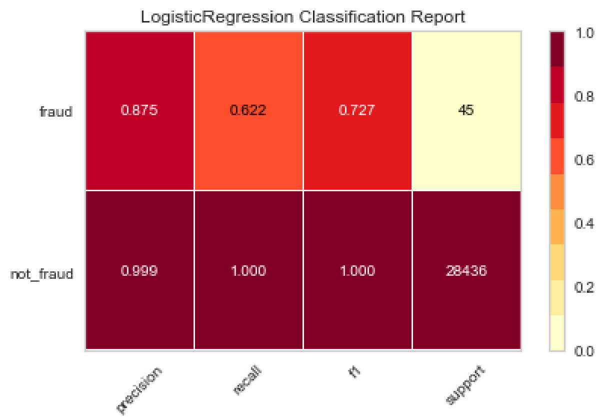
In [88]:
```
print('We have detected ' + str(matrix[1][1]) + ' frauds / ' +
      str(matrix[1][1]+matrix[1][0]) + ' total frauds.')
print('\nSo, the probability to detect a fraud is ' +
      str(matrix[1][1]/(matrix[1][1]+matrix[1][0])))
print("the accuracy is : "+str((matrix[0][0]+matrix[1][1]) /
                               (sum(matrix[0]) + sum(matrix[1]))))
```

```
We have detected 28 frauds / 45 total frauds.

So, the probability to detect a fraud is 0.6222222222222222
the accuracy is : 0.9992626663389628
```

In [89]:
```python
print(classification_report(Yval, prediction_lasso2))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     28436
           1       0.88      0.62      0.73        45

    accuracy                           1.00     28481
   macro avg       0.94      0.81      0.86     28481
weighted avg       1.00      1.00      1.00     28481
```

In [90]:
```python
visualizer = ClassificationReport(model_lasso2, classes = class_names, support = True)
visualizer.fit( Xtrain, Ytrain)        # Fit the visualizer and the model
visualizer.score(Xval, Yval)        # Evaluate the model on the test data
visualizer.show()
```




```
<matplotlib.axes._subplots.AxesSubplot at 0x1d9a42bb580>
```

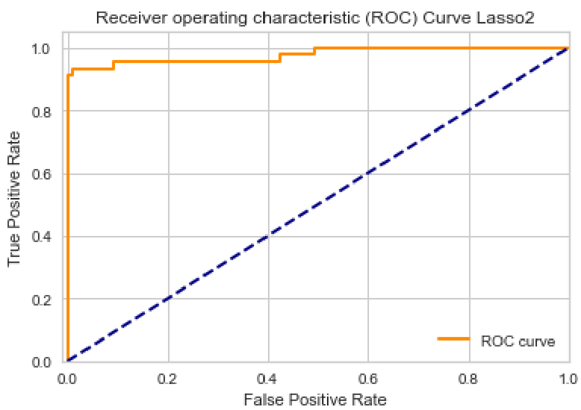
In [91]:
```python
# evaluation
# calculate average error and standard deviation


testYDiff = np.abs(Yval-prediction_lasso2)
avgErr = np.mean(testYDiff)
stdErr = np.std(testYDiff)

print('Logistic regression average error: {} ({})'.format(avgErr, stdErr))
```

```
Logistic regression average error: 0.0007373336610371826 (0.027143875922746998)
```

In [92]:

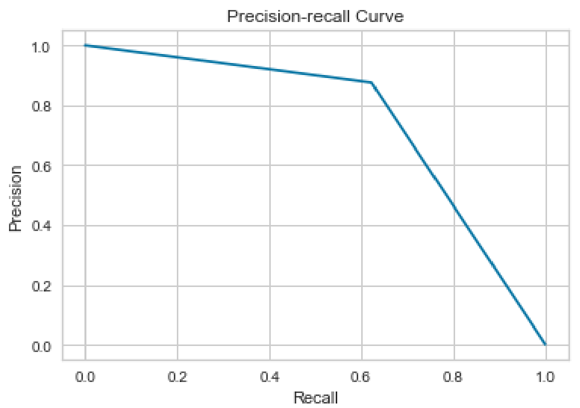
```
#AUC CURVE
fpr2, tpr2, thresholds = roc_curve(Yval, model_lasso2.predict_proba(Xval)[:,1])
print('Logistic Regression AUC: {}'.format(auc(fpr2, tpr2)))

plt.figure()
lw = 2
plt.plot(fpr2, tpr2, color='darkorange',
         lw=lw, label='ROC curve')
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([-0.01, 1.0])
plt.ylim([0.0, 1.05])

plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic (ROC) Curve Lasso2')
plt.legend(loc="lower right")
plt.show()
```

```
Logistic Regression AUC: 0.9773221737703381
```



In [93]:

```
precision, recall, _ = precision_recall_curve(Yval, model_lasso2.predict(Xval))
plt.plot(recall, precision)

plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("Precision-recall Curve")
plt.show()
```



2.6 Logistic regression -- with Elastic Net Penalization

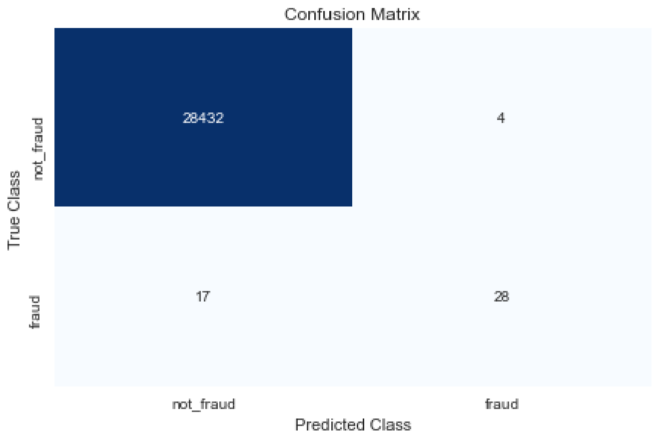
In [94]:
```
###############Logistic regression -- with Elastic Net Penalization ###################
model_en = LogisticRegression(penalty = "elasticnet",solver = "saga", l1_ratio =0.425)
model_en.fit(Xtrain, Ytrain)
print('Validation score: ', model_en.score(Xval,Yval))
```

```
Validation score:  0.9992626663389628
```

In [95]:
```
prediction_en = model_en.predict(Xval)
r2_score(Yval, prediction_en)
```

```
0.5325948328409997
```

In [96]:
```
class_names = ['not_fraud', 'fraud']
matrix = confusion_matrix(Yval, prediction_en)
# Create pandas dataframe
dataframe = pd.DataFrame(matrix, index=class_names, columns=class_names)
# Create heatmap
sns.heatmap(dataframe, annot=True, cbar=None, cmap="Blues", fmt = 'g')
plt.title("Confusion Matrix"), plt.tight_layout()
plt.ylabel("True Class"), plt.xlabel("Predicted Class")
plt.show()
```



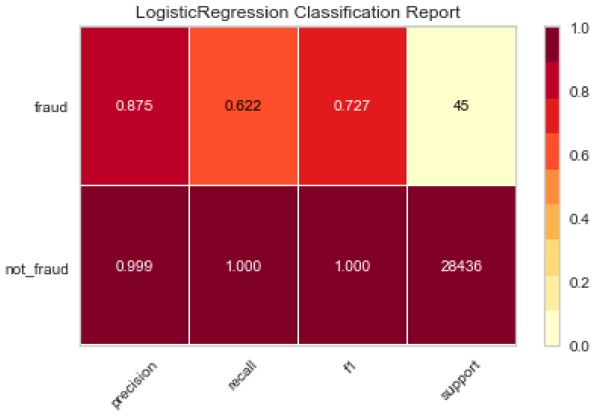
In [97]:
```
print('We have detected ' + str(matrix[1][1]) + ' frauds / ' +
      str(matrix[1][1]+matrix[1][0]) + ' total frauds.')
print('\nSo, the probability to detect a fraud is ' +
      str(matrix[1][1]/(matrix[1][1]+matrix[1][0])))
print("the accuracy is : "+str((matrix[0][0]+matrix[1][1]) /
                               (sum(matrix[0]) + sum(matrix[1]))))
```

```
We have detected 28 frauds / 45 total frauds.

So, the probability to detect a fraud is 0.6222222222222222
the accuracy is : 0.9992626663389628
```

In [98]:
```
print(classification_report(Yval, prediction_en))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     28436
           1       0.88      0.62      0.73        45

    accuracy                           1.00     28481
   macro avg       0.94      0.81      0.86     28481
weighted avg       1.00      1.00      1.00     28481
```

In [99]:
```
visualizer = ClassificationReport(model_en, classes = class_names, support = True)
visualizer.fit( Xtrain, Ytrain)        # Fit the visualizer and the model
visualizer.score(Xval, Yval)        # Evaluate the model on the test data
visualizer.show()
```




```
<matplotlib.axes._subplots.AxesSubplot at 0x1d9acd91bb0>
```

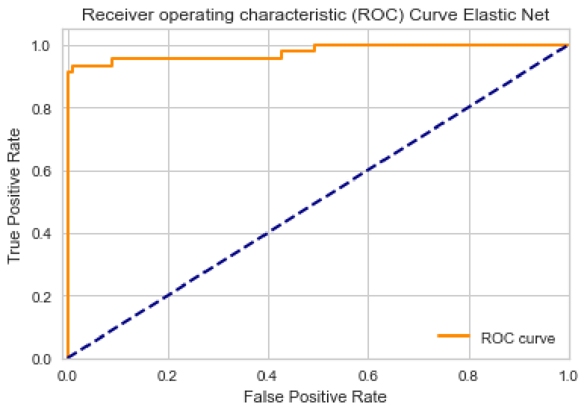
In [100]:
```
# evaluation
# calculate average error and standard deviation
testYDiff = np.abs(Yval-prediction_en)
avgErr = np.mean(testYDiff)
stdErr = np.std(testYDiff)

print('Logistic regression average error: {} ({})'.format(avgErr, stdErr))
```

```
Logistic regression average error: 0.0007373336610371826 (0.027143875922746998)
```

In [101]:

```
#AUC CURVE
fpr2, tpr2, thresholds = roc_curve(Yval, model_en.predict_proba(Xval)[:,1])
print('Logistic Regression AUC: {}'.format(auc(fpr2, tpr2)))

plt.figure()
lw = 2
plt.plot(fpr2, tpr2, color='darkorange',
         lw=lw, label='ROC curve')
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([-0.01, 1.0])
plt.ylim([0.0, 1.05])

plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic (ROC) Curve Elastic Net')
plt.legend(loc="lower right")
plt.show()
```

```
Logistic Regression AUC: 0.9772018255419578
```



Testing: Finding Best Logistic Regression Model

AUC Score

In [102]:

```python
#results of validation sample
fpr2, tpr2, thresholds = roc_curve(Yval, model.predict_proba(Xval)[:,1])
fpr21, tpr21, thresholds = roc_curve(Yval, model_ridge.predict_proba(Xval)[:,1])
fpr22, tpr22, thresholds = roc_curve(Yval, model_ridge2.predict_proba(Xval)[:,1])
fpr23, tpr23, thresholds = roc_curve(Yval, model_lasso.predict_proba(Xval)[:,1])
fpr24, tpr24, thresholds = roc_curve(Yval, model_lasso2.predict_proba(Xval)[:,1])
fpr25, tpr25, thresholds = roc_curve(Yval, model_en.predict_proba(Xval)[:,1])

models = pd.DataFrame({
    'Model': ['Simple Logistic Regression', 'Ridge.1 Logistic Regression',
              'Ridge.2 Logistic Regression', 'Lasso.1 Logistic Regression',
              'Lasso.2 Logistic Regression',
              'Elastic Net Logistic Regression'],
    'AUC Score': [auc(fpr2, tpr2), auc(fpr21, tpr21),auc(fpr22, tpr22),
                  auc(fpr23, tpr23), auc(fpr24, tpr24), auc(fpr25, tpr25)]})

models.sort_values(by='AUC Score', ascending=False)
```

	Model	AUC Score
4	Lasso.2 Logistic Regression	0.977322
5	Elastic Net Logistic Regression	0.977202
1	Ridge.1 Logistic Regression	0.975684
2	Ridge.2 Logistic Regression	0.964614
3	Lasso.1 Logistic Regression	0.964371
0	Simple Logistic Regression	0.963139

Precision

In [103]:

```python
precision_simple = precision_score(Yval, model.predict(Xval))
precision_ridge = precision_score(Yval, model_ridge.predict(Xval))
precision_ridge2 = precision_score(Yval, model_ridge2.predict(Xval))
precision_lasso = precision_score(Yval, model_lasso.predict(Xval))
precision_lasso2 = precision_score(Yval, model_lasso2.predict(Xval))
precision_en = precision_score(Yval, model_en.predict(Xval))

models = pd.DataFrame({
    'Model': ['Simple Logistic Regression', 'Ridge.1 Logistic Regression',
              'Ridge.2 Logistic Regression', 'Lasso.1 Logistic Regression',
              'Lasso2 Logistic Regression',
              'Elastic Net Logistic Regression'],

    'Precision': [precision_simple,precision_ridge, precision_ridge2,
                  precision_lasso, precision_lasso2, precision_en ]})
models.sort_values(by='Precision', ascending=False)
```

	Model	Precision
1	Ridge.1 Logistic Regression	0.875000
4	Lasso2 Logistic Regression	0.875000
5	Elastic Net Logistic Regression	0.875000
0	Simple Logistic Regression	0.848485
2	Ridge.2 Logistic Regression	0.843750
3	Lasso.1 Logistic Regression	0.838710

Recall

In [104]:
```
recall_simple = recall_score(Yval, model.predict(Xval))
recall_ridge = recall_score(Yval, model_ridge.predict(Xval))
recall_ridge2 = recall_score(Yval, model_ridge2.predict(Xval))
recall_lasso = recall_score(Yval, model_lasso.predict(Xval))
recall_lasso2 = recall_score(Yval, model_lasso2.predict(Xval))
recall_en = recall_score(Yval, model_en.predict(Xval))


models = pd.DataFrame({
    'Model': ['Simple Logistic Regression', 'Ridge.1 Logistic Regression',
              'Ridge.2 Logistic Regression', 'Lasso.1 Logistic Regression',
              'Lasso2 Logistic Regression',
              'Elastic Net Logistic Regression'],

    'Recall': [recall_simple,recall_ridge, recall_ridge2,recall_lasso,
               recall_lasso2, recall_en ]})
models.sort_values(by='Recall', ascending=False)
```

	Model	Recall
0	Simple Logistic Regression	0.622222
1	Ridge.1 Logistic Regression	0.622222
4	Lasso2 Logistic Regression	0.622222
5	Elastic Net Logistic Regression	0.622222
2	Ridge.2 Logistic Regression	0.600000
3	Lasso.1 Logistic Regression	0.577778

Analysis: On testing Sample

In [105]:
```
#results over testing sample as we choose Lasso2 model as our best model
# Prediction on test data
pred_logit = model_lasso2.predict(Xtest)
score_logit = model_lasso2.predict_proba(Xtest)[:,1]
```

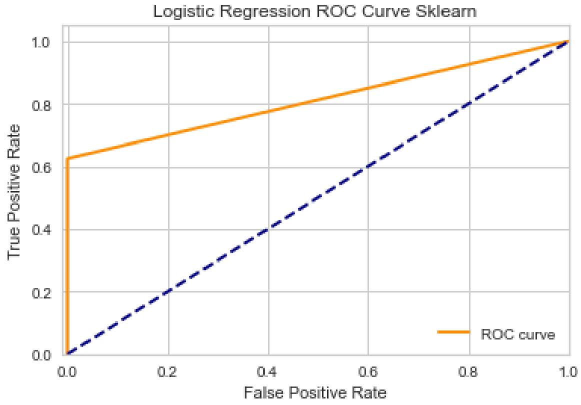
AUC Score

In [106]:
```
fpr2, tpr2, thresholds = roc_curve(Ytest, pred_logit)
auc_logit = auc(fpr2, tpr2)
print('Logistic Model AUC for testing sample: {}'.format(auc_logit))
```

```
Logistic Model AUC for testing sample: 0.8121790993116127
```

In [107]:

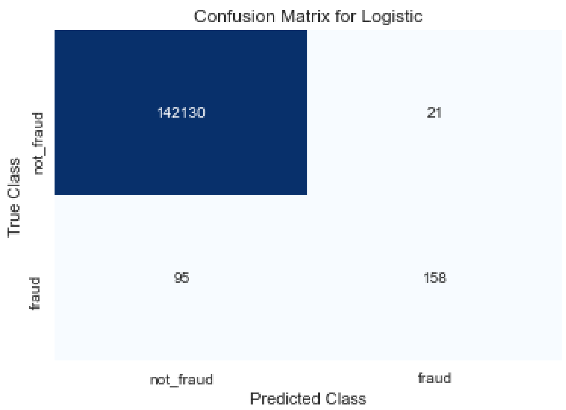
```
plt.figure()
lw = 2
plt.plot(fpr2, tpr2, color='darkorange',
         lw=lw, label='ROC curve')
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([-0.01, 1.0])
plt.ylim([0.0, 1.05])

plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Logistic Regression ROC Curve Sklearn')
plt.legend(loc="lower right")
plt.show()
```



Precision&Recall

In [109]:

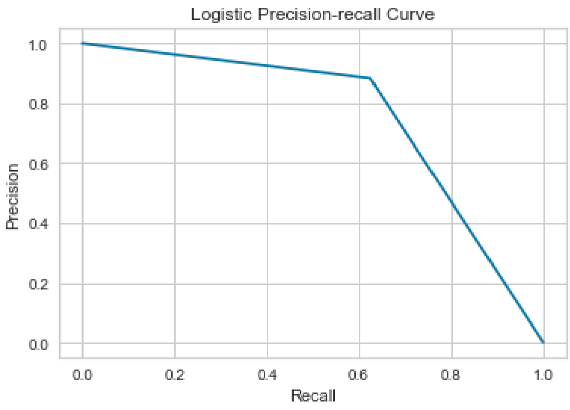
```
# precision and recall, confusion matrics
class_names = ['not_fraud', 'fraud']
matrix_logit = confusion_matrix(Ytest, pred_logit)
dataframe = pd.DataFrame(matrix_logit, index=class_names, columns=class_names)

# Create heatmap
plt.figure()
sns.heatmap(dataframe, annot=True, cbar=None, cmap="Blues", fmt = 'g')
plt.title("Confusion Matrix for Logistic")
plt.ylabel("True Class"), plt.xlabel("Predicted Class")
plt.show()
```



In [110]:
```
print('We have detected ' + str(matrix_logit[1][1]) + ' frauds / ' +
      str(matrix_logit[1][1]+matrix_logit[1][0]) + ' total frauds.')
print('\nSo, the probability to detect a fraud is ' +
      str(matrix_logit[1][1]/(matrix_logit[1][1]+matrix_logit[1][0])))
print("the accuracy is : "+ str((matrix_logit[0][0] + matrix_logit[1][1]) /
                                (sum(matrix_logit[0]) + sum(matrix_logit[1]))))
```

```
We have detected 158 frauds / 253 total frauds.

So, the probability to detect a fraud is 0.6245059288537549
the accuracy is : 0.9991854161399961
```

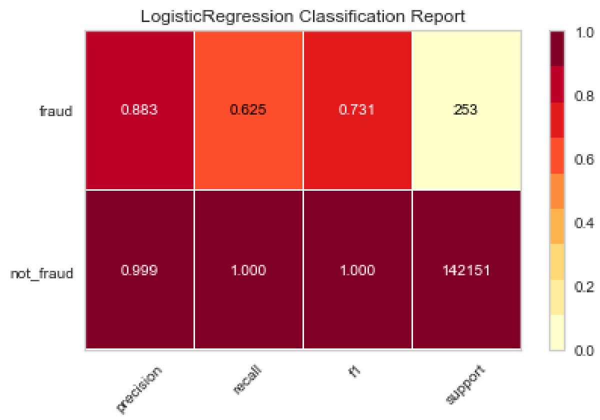
In [111]:
```
precision, recall, _ = precision_recall_curve(Ytest, pred_logit)
plt.plot(recall, precision)

plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("Logistic Precision-recall Curve")
plt.show()
```



In [112]:
```
print(classification_report(Ytest, pred_logit))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00    142151
           1       0.88      0.62      0.73       253

    accuracy                           1.00    142404
   macro avg       0.94      0.81      0.87    142404
weighted avg       1.00      1.00      1.00    142404
```

In [114]:
```
visualizer_logit = ClassificationReport(model_lasso2, classes = class_names,
                                        support = True)
visualizer_logit.fit( Xtrain, Ytrain)        # Fit the visualizer and the model
visualizer_logit.score(Xtest, Ytest)        # Evaluate the model on the test data
visualizer_logit.show()
```




```
<matplotlib.axes._subplots.AxesSubplot at 0x1d9a45b8280>
```

In [117]:
```
# evaluation
# calculate average error and standard deviation
testYDiff_logit = np.abs(Ytest-pred_logit)
avgErr_logit = np.mean(testYDiff_logit)
stdErr_logit = np.std(testYDiff_logit)

print('Logitic Model average error: {} ({})'.format(avgErr_logit, stdErr_logit))
```

```
Logitic Model average error: 0.0008145838600039325 (0.028529288689677385)
```

Conclusion--- Best Logistic Regression Model

In [118]:
```
#results over testing sample
recall_logit = recall_score(Ytest, pred_logit)
precision_logit = precision_score(Ytest, pred_logit)
score_logit = model_lasso2.score(Xtest, Ytest)

logit_model = pd.DataFrame({
    'Model': ['Logistic Regression - Lasso Penalization 2'], #with solver saga
    'AUC Score': [auc_logit],
    'Recall': [recall_logit],
    'Precision': [precision_logit],
    'Accuracy': [score_logit]
})

display(logit_model)
```

	Model	AUC Score	Recall	Precision	Accuracy
0	Logistic Regression - Lasso Penalization 2	0.812179	0.624506	0.882682	0.999185

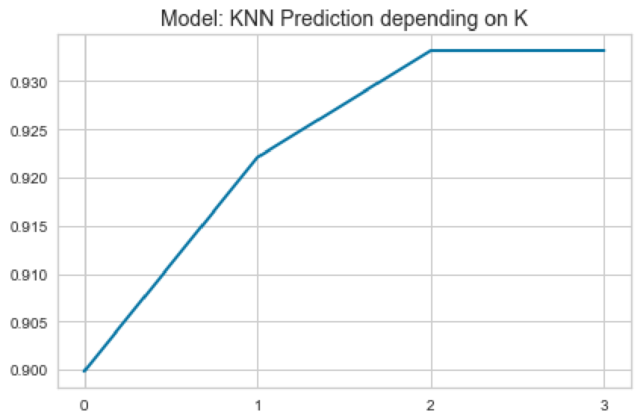
3.K-Nearest Neighbors

Finding Best Model with different learning rate K

In [119]:
```python
########KNeighborsClassifiers using the sklearn, finding the best k########
knn_score = []

for i in range(1,5,1):
    model_knn =  KNeighborsClassifier(n_neighbors=i,
                                      weights = "distance").fit(Xtrain, Ytrain)
    score_val = model_knn.predict_proba(Xval)[:,1]
    fpr, tpr, thresholds = roc_curve(Yval, score_val)
    knn_score.append(np.around(auc(fpr, tpr),5))
```

In [120]:
```python
# plot the AUC grapp

plt.plot(knn_score,lw=2)
x_major_locator=MultipleLocator(1)
ax=plt.gca()
ax.xaxis.set_major_locator(x_major_locator)
plt.title("Model: KNN Prediction depending on K", size = 14)
plt.tight_layout()

# get the optimal alpha
print("The alpha giving the best AUC is",knn_score.index(np.max(knn_score))+1)
```

```
The alpha giving the best AUC is 4
```



Analysis: On testing Sample

In [121]:
```python
#from above plot, we go with K=4
model_knn =  KNeighborsClassifier(n_neighbors=4,
                                  weights = "distance").fit(Xtrain, Ytrain)

print('Validation score from KNN: ', model_knn.score(Xval,Yval))
```

```
Validation score from KNN:  0.9995435553526912
```

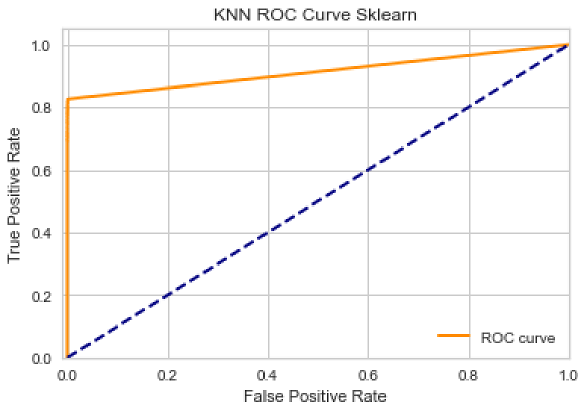
In [122]:
```python
# Prediction on test data
score_knn = model_knn.predict_proba(Xtest)[:,1]
Ypred_knn = model_knn.predict(Xtest)
```

AUC Score

In [123]:

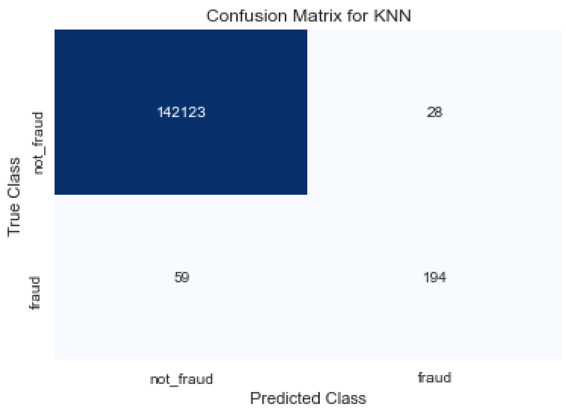
```
#AUC CURVE
fpr, tpr, thresholds = roc_curve(Ytest, score_knn)
auc_knn = auc(fpr, tpr)
print('KNN Model AUC for testing sample: {}'.format(auc_knn))

plt.figure()
lw = 2
plt.plot(fpr, tpr, color='darkorange',
         lw=lw, label='ROC curve')
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([-0.01, 1.0])
plt.ylim([0.0, 1.05])

plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('KNN ROC Curve Sklearn')
plt.legend(loc="lower right")
plt.show()
```

```
KNN Model AUC for testing sample: 0.9128844034163638
```



Precision&Recall

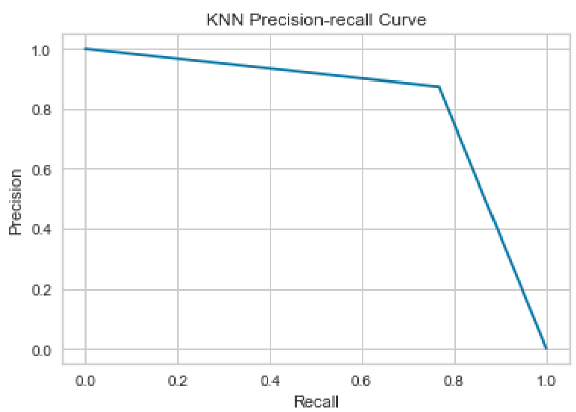
In [124]:
```python
# precision and recall, confusion matrics
class_names = ['not_fraud', 'fraud']
matrix_knn = confusion_matrix(Ytest, Ypred_knn)
dataframe = pd.DataFrame(matrix_knn, index=class_names, columns=class_names)

# Create heatmap
plt.figure()
sns.heatmap(dataframe, annot=True, cbar=None, cmap="Blues", fmt = 'g')
plt.title("Confusion Matrix for KNN")
plt.ylabel("True Class"), plt.xlabel("Predicted Class")
plt.show()
```



In [125]:
```python
print('We have detected ' + str(matrix_knn[1][1]) + ' frauds / ' +
      str(matrix_knn[1][1]+matrix_knn[1][0]) + ' total frauds.')
print('\nSo, the probability to detect a fraud is ' +
      str(matrix_knn[1][1]/(matrix_knn[1][1]+matrix_knn[1][0])))
print("the accuracy is : "+ str((matrix_knn[0][0] + matrix_knn[1][1]) /
                                (sum(matrix_knn[0]) + sum(matrix_knn[1]))))
```

```
We have detected 194 frauds / 253 total frauds.

So, the probability to detect a fraud is 0.766798418972332
the accuracy is : 0.999389062104997
```

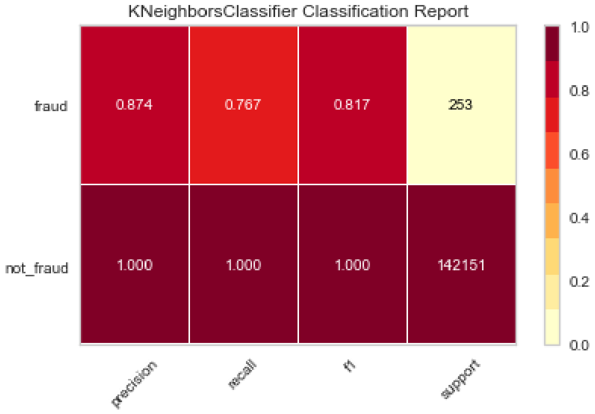
In [126]:
```python
precision, recall, _ = precision_recall_curve(Ytest, Ypred_knn)
plt.plot(recall, precision)

plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("KNN Precision-recall Curve")
plt.show()
```



In [127]:
```python
print(classification_report(Ytest, Ypred_knn))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00    142151
           1       0.87      0.77      0.82       253

    accuracy                           1.00    142404
   macro avg       0.94      0.88      0.91    142404
weighted avg       1.00      1.00      1.00    142404
```

In [128]:
```python
visualizer_knn = ClassificationReport(model_knn, classes = class_names,
                                      support = True)
visualizer_knn.fit( Xtrain, Ytrain)        # Fit the visualizer and the model
visualizer_knn.score(Xtest, Ytest)        # Evaluate the model on the test data
visualizer_knn.show()
```




```
<matplotlib.axes._subplots.AxesSubplot at 0x1d9a269c190>
```

In [129]:
```python
# evaluation
# calculate average error and standard deviation
testYDiff_knn = np.abs(Ytest-Ypred_knn)
avgErr_knn = np.mean(testYDiff_knn)
stdErr_knn = np.std(testYDiff_knn)

print('KNN average error: {} ({})'.format(avgErr_knn, stdErr_knn))
```

```
KNN average error: 0.0006109378950029493 (0.024709606429310017)
```

conclusion---Best KNN Model

In [130]:
```python
precision_knn = matrix_knn[1][1]/(matrix_knn[1][1]+matrix_knn[0][1])
recall_knn = matrix_knn[1][1]/(matrix_knn[1][1]+matrix_knn[1][0])
acc_knn = (matrix_knn[0][0] + matrix_knn[1][1])/(sum(matrix_knn[0])+sum(matrix_knn[1]))

knn_model = pd.DataFrame({
    'Model': ['KNearestNeighbors Model'],
    'AUC Score': [auc_knn],
    'Recall': [recall_knn],
    'Precision': [precision_knn],
    'Accuracy': [acc_knn]
})

display(knn_model)
```

	Model	AUC Score	Recall	Precision	Accuracy
0	KNearestNeighbors Model	0.912884	0.766798	0.873874	0.999389

4. Feed-Forward Neural Networks

4.1 4 Models with different hyperparameters

Model 1

In [139]:
```python
model1 =  keras.Sequential([
Dense(input_dim = 29, units = 256, activation = "sigmoid"),
Dense(units = 128, activation = "sigmoid"),
Dense(units = 64, activation = "sigmoid"),
Dense(units =1, activation = "sigmoid"),])
```

In [140]:
```python
model1.compile(optimizer=keras.optimizers.RMSprop(learning_rate=1e-3),
               loss = "binary_crossentropy")
model1.fit(Xtrain.astype(np.float32), Ytrain, batch_size = 15, epochs = 10)
```

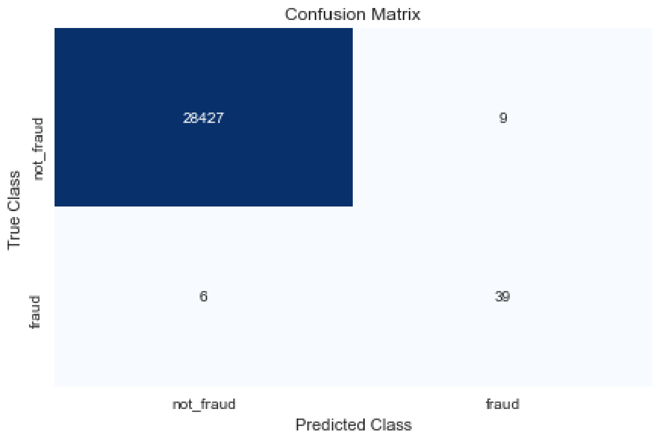
```
Epoch 1/10
7595/7595 [==============================] - 21s 3ms/step - loss: 0.0103
Epoch 2/10
7595/7595 [==============================] - 13s 2ms/step - loss: 0.0085
Epoch 3/10
7595/7595 [==============================] - 14s 2ms/step - loss: 0.0071
Epoch 4/10
7595/7595 [==============================] - 13s 2ms/step - loss: 0.0066
Epoch 5/10
7595/7595 [==============================] - 16s 2ms/step - loss: 0.0065
Epoch 6/10
7595/7595 [==============================] - 16s 2ms/step - loss: 0.0067
Epoch 7/10
7595/7595 [==============================] - 16s 2ms/step - loss: 0.0066
Epoch 8/10
7595/7595 [==============================] - 17s 2ms/step - loss: 0.0062
Epoch 9/10
7595/7595 [==============================] - 16s 2ms/step - loss: 0.0065
Epoch 10/10
7595/7595 [==============================] - 17s 2ms/step - loss: 0.0063
```

```
<tensorflow.python.keras.callbacks.History at 0x1d9aeb7d7c0>
```

In [141]:
```
model1.evaluate(Xval.astype(np.float32), Yval)
```

```
891/891 [==============================] - 1s 1ms/step - loss: 0.0062


0.0061766039580106735
```

In [142]:
```
class_names = ['not_fraud', 'fraud']
y_pred1 = 1*(model1.predict(Xval.astype(np.float32)).flatten() >= 0.5)

matrix = confusion_matrix(Yval, y_pred1)
# Create pandas dataframe
dataframe = pd.DataFrame(matrix, index=class_names, columns=class_names)
# Create heatmap
sns.heatmap(dataframe, annot=True, cbar=None, cmap="Blues", fmt = 'g')
plt.title("Confusion Matrix"), plt.tight_layout()
plt.ylabel("True Class"), plt.xlabel("Predicted Class")
plt.show()
```



In [143]:
```
fpr2, tpr2, thresholds = roc_curve(Yval, y_pred1)

print("R2 of model 1 is:", r2_score(Yval, y_pred1))
print("Accuracy of model 1 is:",np.mean(Yval == y_pred1))
print(classification_report(Yval, y_pred1))
print('Model 1 AUC: {}'.format(auc(fpr2, tpr2)))
```

```
R2 of model 1 is: 0.6661391663149998
Accuracy of model 1 is: 0.9994733330992591
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     28436
           1       0.81      0.87      0.84        45

    accuracy                           1.00     28481
   macro avg       0.91      0.93      0.92     28481
weighted avg       1.00      1.00      1.00     28481

Model 1 AUC: 0.9331750832278333
```

MODEL 2

In [144]:
```
model2 =  keras.Sequential([
Dense(input_dim = 29, units = 8, activation = "relu"),
Dense(units = 10, activation = "relu"),
Dense(units = 12, activation = "relu"),
Dense(units =1, activation = "sigmoid"),])
```

In [145]:

```python
model2.compile(optimizer=keras.optimizers.RMSprop(learning_rate=1e-3),
                loss = "binary_crossentropy")
model2.fit(Xtrain.astype(np.float32), Ytrain, batch_size = 15, epochs = 10)
```

```
Epoch 1/10
7595/7595 [==============================] - 14s 2ms/step - loss: 0.0612
Epoch 2/10
7595/7595 [==============================] - 13s 2ms/step - loss: 0.0081
Epoch 3/10
7595/7595 [==============================] - 13s 2ms/step - loss: 0.0098
Epoch 4/10
7595/7595 [==============================] - 14s 2ms/step - loss: 0.0095
Epoch 5/10
7595/7595 [==============================] - 13s 2ms/step - loss: 0.0106
Epoch 6/10
7595/7595 [==============================] - 12s 2ms/step - loss: 0.0089
Epoch 7/10
7595/7595 [==============================] - 12s 2ms/step - loss: 0.0081
Epoch 8/10
7595/7595 [==============================] - 13s 2ms/step - loss: 0.0081
Epoch 9/10
7595/7595 [==============================] - 13s 2ms/step - loss: 0.0084
Epoch 10/10
7595/7595 [==============================] - 12s 2ms/step - loss: 0.0075
```

```
<tensorflow.python.keras.callbacks.History at 0x1d9a48bcf70>
```

In [146]:

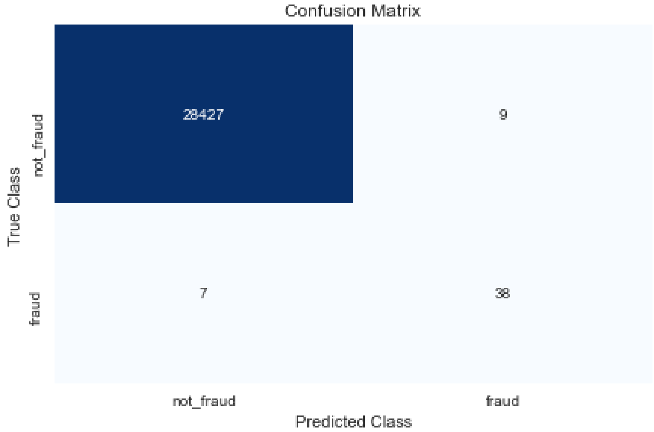
```python
model2.evaluate(Xval.astype(np.float32), Yval)
```

```
891/891 [==============================] - 1s 1ms/step - loss: 0.0087
```

```
0.008662054315209389
```

In [147]:

```python
class_names = ['not_fraud', 'fraud']
y_pred2 = 1*(model2.predict(Xval.astype(np.float32)).flatten() >= 0.5)

matrix = confusion_matrix(Yval, y_pred2)
# Create pandas dataframe
dataframe = pd.DataFrame(matrix, index=class_names, columns=class_names)

# Create heatmap
sns.heatmap(dataframe, annot=True, cbar=None, cmap="Blues", fmt = 'g')
plt.title("Confusion Matrix"), plt.tight_layout()
plt.ylabel("True Class"), plt.xlabel("Predicted Class")
plt.show()
```



In [148]:
```python
fpr2, tpr2, thresholds = roc_curve(Yval, y_pred2)
print("R2 of model 2 is:", r2_score(Yval, y_pred2))
print("Accuracy of model 2 is:",np.mean(Yval == y_pred2))
print(classification_report(Yval, y_pred2))
print('Model 2 AUC: {}'.format(auc(fpr2, tpr2)))
```

```
R2 of model 2 is: 0.6438817774026665
Accuracy of model 2 is: 0.9994382219725431
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     28436
           1       0.81      0.84      0.83        45

    accuracy                           1.00     28481
   macro avg       0.90      0.92      0.91     28481
weighted avg       1.00      1.00      1.00     28481

Model 2 AUC: 0.9220639721167221
```

MODEL 3

In [149]:
```python
model3 =  keras.Sequential([
Dense(input_dim = 29, units = 8, activation = "relu"),
Dense(units = 40, activation = "relu"),
Dense(units = 42, activation = "linear"),
Dense(units = 44, activation = "relu"),
Dense(units =1, activation = "sigmoid"),])
```

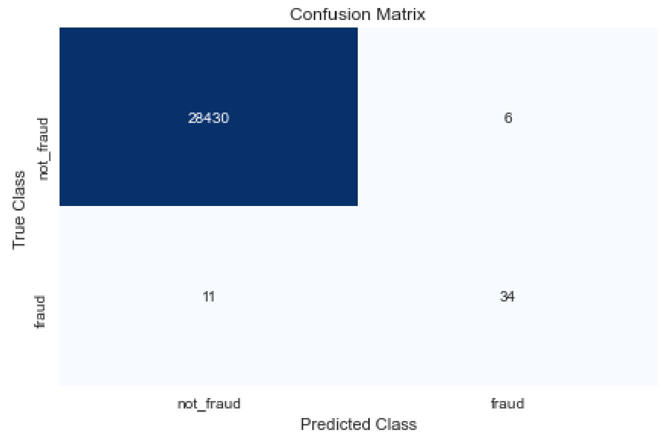
In [150]:
```python
model3.compile(optimizer="adam", loss = "binary_crossentropy")
model3.fit(Xtrain.astype(np.float32), Ytrain, batch_size = 15, epochs = 10)
```

```
Epoch 1/10
7595/7595 [==============================] - 15s 2ms/step - loss: 0.0207
Epoch 2/10
7595/7595 [==============================] - 14s 2ms/step - loss: 0.0026
Epoch 3/10
7595/7595 [==============================] - 14s 2ms/step - loss: 0.0034
Epoch 4/10
7595/7595 [==============================] - 14s 2ms/step - loss: 0.0040
Epoch 5/10
7595/7595 [==============================] - 14s 2ms/step - loss: 0.0028
Epoch 6/10
7595/7595 [==============================] - 14s 2ms/step - loss: 0.0031
Epoch 7/10
7595/7595 [==============================] - 14s 2ms/step - loss: 0.0032
Epoch 8/10
7595/7595 [==============================] - 13s 2ms/step - loss: 0.0032
Epoch 9/10
7595/7595 [==============================] - 14s 2ms/step - loss: 0.0031
Epoch 10/10
7595/7595 [==============================] - 14s 2ms/step - loss: 0.0024

<tensorflow.python.keras.callbacks.History at 0x1d9b0a0e5b0>
```

In [151]:
```python
model3.evaluate(Xval.astype(np.float32), Yval)
```

```
891/891 [==============================] - 1s 1ms/step - loss: 0.0036

0.0035812901332974434
```

```
In [152]: class_names = ['not_fraud', 'fraud']
          y_pred3 = 1*(model3.predict(Xval.astype(np.float32)).flatten() >= 0.5)

          matrix = confusion_matrix(Yval, y_pred3)
          # Create pandas dataframe
          dataframe = pd.DataFrame(matrix, index=class_names, columns=class_names)
          # Create heatmap
          sns.heatmap(dataframe, annot=True, cbar=None, cmap="Blues", fmt = 'g')
          plt.title("Confusion Matrix"), plt.tight_layout()
          plt.ylabel("True Class"), plt.xlabel("Predicted Class")
          plt.show()
```




```
In [153]: fpr2, tpr2, thresholds = roc_curve(Yval, y_pred3)

          print("R2 of model 3 is:", r2_score(Yval, y_pred3))
          print("Accuracy of model 3 is:",np.mean(Yval == y_pred3))
          print(classification_report(Yval, y_pred3))
          print('Model 3 AUC: {}'.format(auc(fpr2, tpr2)))
```

```
R2 of model 3 is: 0.6216243884903332
Accuracy of model 3 is: 0.999403110845827
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     28436
           1       0.85      0.76      0.80        45

    accuracy                           1.00     28481
   macro avg       0.92      0.88      0.90     28481
weighted avg       1.00      1.00      1.00     28481

Model 3 AUC: 0.8776722777074444
```

MODEL 4

```
In [154]: model4 =  keras.Sequential([
          Dense(input_dim = 29, units = 28, activation = "relu"),
          Dense(units = 10, activation = "relu"),
          Dense(units = 12, activation = "relu"),
          Dense(units =1, activation = "sigmoid"),])
```

In [155]:
```
model4.compile(keras.optimizers.RMSprop(learning_rate=1e-3),
               loss = "binary_crossentropy")
model4.fit(Xtrain.astype(np.float32), Ytrain, batch_size = 15, epochs = 10)
```

```
Epoch 1/10
7595/7595 [==============================] - 13s 2ms/step - loss: 0.0619
Epoch 2/10
7595/7595 [==============================] - 13s 2ms/step - loss: 0.0095
Epoch 3/10
7595/7595 [==============================] - 12s 2ms/step - loss: 0.0119
Epoch 4/10
7595/7595 [==============================] - 13s 2ms/step - loss: 0.0113
Epoch 5/10
7595/7595 [==============================] - 12s 2ms/step - loss: 0.0101
Epoch 6/10
7595/7595 [==============================] - 12s 2ms/step - loss: 0.0081
Epoch 7/10
7595/7595 [==============================] - 12s 2ms/step - loss: 0.0095
Epoch 8/10
7595/7595 [==============================] - 12s 2ms/step - loss: 0.0087
Epoch 9/10
7595/7595 [==============================] - 13s 2ms/step - loss: 0.0074
Epoch 10/10
7595/7595 [==============================] - 12s 2ms/step - loss: 0.0079
```

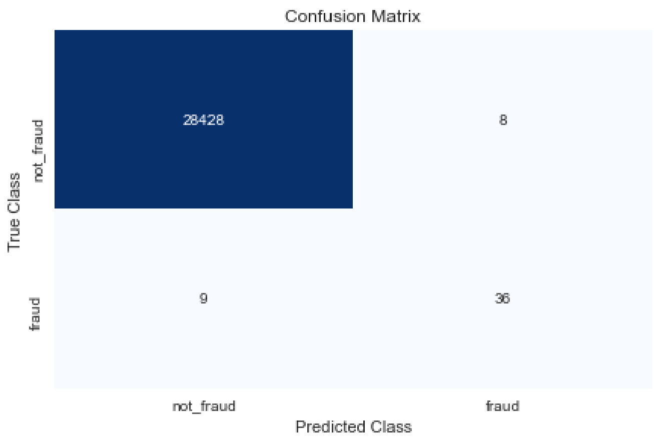
```
<tensorflow.python.keras.callbacks.History at 0x1d9b1e9b520>
```

In [156]:
```
model4.evaluate(Xval.astype(np.float32), Yval)
```

```
891/891 [==============================] - 1s 1ms/step - loss: 0.0097
```

```
0.009652191773056984
```

In [157]:
```
class_names = ['not_fraud', 'fraud']
y_pred4 = 1*(model4.predict(Xval.astype(np.float32)).flatten() >= 0.5)

matrix = confusion_matrix(Yval, y_pred4)
# Create pandas dataframe
dataframe = pd.DataFrame(matrix, index=class_names, columns=class_names)
# Create heatmap
sns.heatmap(dataframe, annot=True, cbar=None, cmap="Blues", fmt = 'g')
plt.title("Confusion Matrix"), plt.tight_layout()
plt.ylabel("True Class"), plt.xlabel("Predicted Class")
plt.show()
```



In [158]:

```
fpr2, tpr2, thresholds = roc_curve(Yval, y_pred4)
print("R2 of model 4 is:", r2_score(Yval, y_pred4))
print("Accuracy of model 4 is:",np.mean(Yval == y_pred4))
print(classification_report(Yval, y_pred4))
print('Model 4 AUC: {}'.format(auc(fpr2, tpr2)))
```

```
R2 of model 4 is: 0.6216243884903332
Accuracy of model 4 is: 0.999403110845827
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     28436
           1       0.82      0.80      0.81        45

    accuracy                           1.00     28481
   macro avg       0.91      0.90      0.90     28481
weighted avg       1.00      1.00      1.00     28481

Model 4 AUC: 0.8998593332395555
```

Finding Best FNN Model

AUC

In [159]:

```
#results of validation sample
fpr23, tpr23, thresholds = roc_curve(Yval, y_pred1)
fpr2, tpr2, thresholds = roc_curve(Yval, y_pred2)
fpr21, tpr21, thresholds = roc_curve(Yval, y_pred3)
fpr22, tpr22, thresholds = roc_curve(Yval, y_pred4)

models = pd.DataFrame({
    'Model': ['FNN Model 1', 'FNN Model 2', 'FNN Model 3', 'FNN Model 4'],
    'AUC Score': [auc(fpr23, tpr23),auc(fpr2, tpr2),
                  auc(fpr21, tpr21),auc(fpr22, tpr22)]})

models.sort_values(by='AUC Score', ascending=False)
```

	Model	AUC Score
0	FNN Model 1	0.933175
1	FNN Model 2	0.922064
3	FNN Model 4	0.899859
2	FNN Model 3	0.877672

Precision

In [160]:

```
precision_0 = precision_score(Yval, y_pred1)
precision_1 = precision_score(Yval, y_pred2)
precision_2 = precision_score(Yval, y_pred3)
precision_3 = precision_score(Yval, y_pred4)

models = pd.DataFrame({
    'Model': ['FNN Model 1', 'FNN Model 2', 'FNN Model 3', 'FNN Model 4'],
    'Precision': [precision_0,precision_1, precision_2,precision_3]})

models.sort_values(by='Precision', ascending=False)
```

	Model	Precision
2	FNN Model 3	0.850000
3	FNN Model 4	0.818182
0	FNN Model 1	0.812500
1	FNN Model 2	0.808511

Recall

In [161]:

```
recall_0 = recall_score(Yval, y_pred1)
recall_1 = recall_score(Yval, y_pred2)
recall_2 = recall_score(Yval, y_pred3)
recall_3 = recall_score(Yval, y_pred4)

models = pd.DataFrame({
    'Model': ['FNN Model 1', 'FNN Model 2', 'FNN Model 3', 'FNN Model 4'],
    'Recall': [recall_0,recall_1,recall_2, recall_3 ]})

models.sort_values(by='Recall', ascending=False)
```

	Model	Recall
0	FNN Model 1	0.866667
1	FNN Model 2	0.844444
3	FNN Model 4	0.800000
2	FNN Model 3	0.755556

Analysis: On testing Sample

AUC

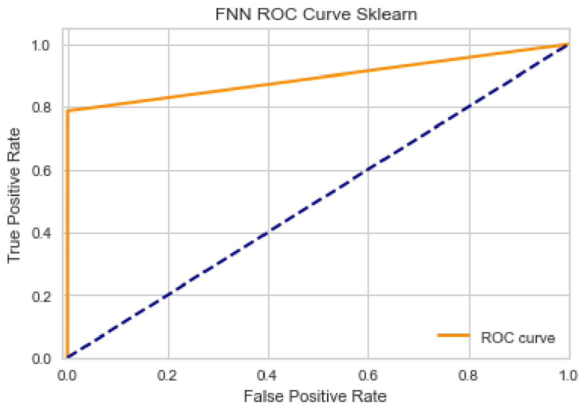
In [162]:

```
#results over testing sample as we choose model 1 as our best model
# Prediction on test data
pred_fnn = 1*(model1.predict(Xtest.astype(np.float32)).flatten() >= 0.5)

fpr2, tpr2, thresholds = roc_curve(Ytest, pred_fnn)
auc_fnn = auc(fpr2, tpr2)
print('FNN Model AUC for testing sample: {}'.format(auc_fnn))
```

```
FNN Model AUC for testing sample: 0.893118832634773
```

In [163]:

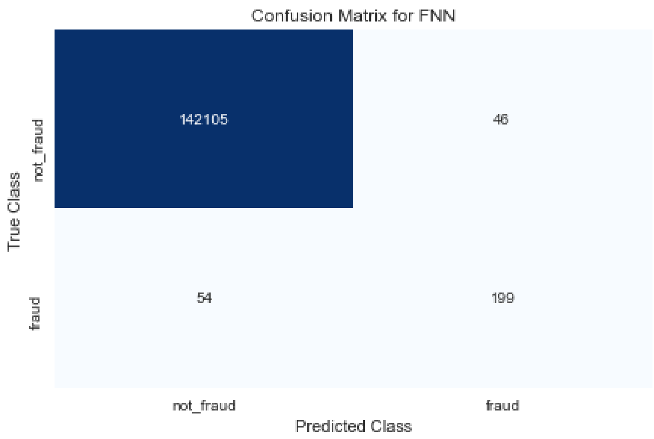
```
plt.figure()
lw = 2
plt.plot(fpr2, tpr2, color='darkorange',
         lw=lw, label='ROC curve')
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([-0.01, 1.0])
plt.ylim([0.0, 1.05])

plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('FNN ROC Curve Sklearn')
plt.legend(loc="lower right")
plt.show()
```



Precision&Recall

In [164]:

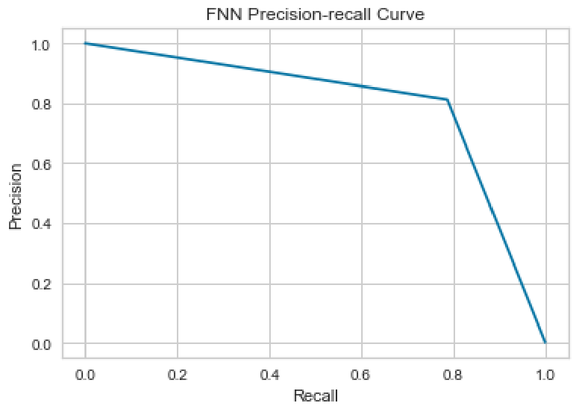
```
# precision and recall, confusion matrics
class_names = ['not_fraud', 'fraud']
matrix_fnn = confusion_matrix(Ytest, pred_fnn)
dataframe = pd.DataFrame(matrix_fnn, index=class_names, columns=class_names)

# Create heatmap
sns.heatmap(dataframe, annot=True, cbar=None, cmap="Blues", fmt = 'g')
plt.title("Confusion Matrix for FNN"), plt.tight_layout()
plt.ylabel("True Class"), plt.xlabel("Predicted Class")
plt.show()
```



In [165]:
```
print('We have detected ' + str(matrix_fnn[1][1]) + ' frauds / ' +
      str(matrix_fnn[1][1]+matrix_fnn[1][0]) + ' total frauds.')
print('\nSo, the probability to detect a fraud is ' +
      str(matrix_fnn[1][1]/(matrix_fnn[1][1]+matrix_fnn[1][0])))
print("the accuracy is : "+ str((matrix_fnn[0][0] + matrix_fnn[1][1]) /
                                (sum(matrix_fnn[0]) + sum(matrix_fnn[1]))))
```

```
We have detected 199 frauds / 253 total frauds.

So, the probability to detect a fraud is 0.7865612648221344
the accuracy is : 0.9992977725344794
```

In [166]:
```
precision, recall, _ = precision_recall_curve(Ytest, pred_fnn)
plt.plot(recall, precision)

plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("FNN Precision-recall Curve")
plt.show()
```



In [167]:
```
print(classification_report(Ytest, pred_fnn))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00    142151
           1       0.81      0.79      0.80       253

    accuracy                           1.00    142404
   macro avg       0.91      0.89      0.90    142404
weighted avg       1.00      1.00      1.00    142404
```

In [168]:
```
# evaluation
# calculate average error and standard deviation
testYDiff_fnn = np.abs(Ytest-pred_fnn)
avgErr_fnn = np.mean(testYDiff_fnn)
stdErr_fnn = np.std(testYDiff_fnn)

print('FNN average error: {} ({})'.format(avgErr_fnn, stdErr_fnn))
```

```
FNN average error: 0.0007022274655206314 (0.026490268819083358)
```

Conclusion---Best FNN Model

In [169]:
```
recall_fnn = recall_score(Ytest, pred_fnn)
precision_fnn = precision_score(Ytest, pred_fnn)
score_fnn = np.mean(Ytest == pred_fnn)

fnn_model = pd.DataFrame({
    'Model': ['FNN Model 1'], #best model
    'AUC Score': [auc_fnn],
    'Recall': [recall_fnn],
    'Precision': [precision_fnn],
    'Accuracy': [score_fnn]
})

display(fnn_model)
```

	Model	AUC Score	Recall	Precision	Accuracy
0	FNN Model 1	0.893119	0.786561	0.812245	0.999298

5. Support Vector Machine

5.1 Finding Best Model with different C value

In [172]:
```
#SVM: Optimize with AUC
c_range = [.25, 1, 2, 5]#
frame = pd.DataFrame(columns = ['c_range', 'AUC'])

for c_value in c_range:
    model_svm = svm.SVC(kernel='linear', C=c_value)
    model_svm.fit(X=Xtrain, y=Ytrain)

    #initialize empty
    fpr1 = dict()
    tpr1 = dict()
    lw = 2

    #predictions
    svm_score = model_svm.decision_function(Xval)

    #store false and true positive rate
    fpr1 = roc_curve(Yval, svm_score)[0]
    tpr1 = roc_curve(Yval, svm_score)[1]
    svm_auc = roc_auc_score(Yval, svm_score)

    frame = frame.append({'c_range' : c_value, 'AUC' : svm_auc},ignore_index = True)
    print("Done with: {}, None".format(c_value))

#print('Sklearn AUC: {} '.format(auc))
display(frame)
```

```
Done with: 0.25, None
Done with: 1, None
Done with: 2, None
Done with: 5, None
```

	c_range	AUC
0	0.25	0.951871
1	1.00	0.955309
2	2.00	0.955317
3	5.00	0.955383

In [173]:
```
#So we select C=5
model_svm = svm.SVC(kernel='linear', C=5)
model_svm.fit(X=Xtrain, y=Ytrain)
```

```
SVC(C=5, kernel='linear')
```

Analysis: On testing Sample

In [174]:
```
#predictions
score_svm = model_svm.decision_function(Xtest)
preds_svm = model_svm.predict(Xtest)
```

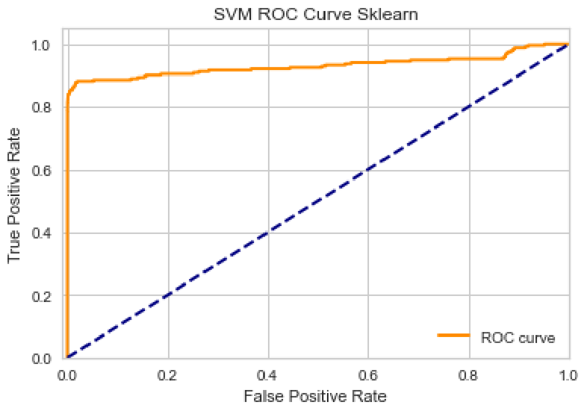
AUC Score

In [175]:
```
#AUC CURVE
fpr, tpr, thresholds = roc_curve(Ytest, score_svm)
auc_svm = metrics.auc(fpr, tpr)
print('SVM Model AUC for testing sample: {}'.format(auc_svm))
```

```
SVM Model AUC for testing sample: 0.9308503235842596
```

In [176]:

```
plt.figure()
lw = 2
plt.plot(fpr, tpr, color='darkorange',
         lw=lw, label='ROC curve')
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([-0.01, 1.0])
plt.ylim([0.0, 1.05])

plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('SVM ROC Curve Sklearn')
plt.legend(loc="lower right")
plt.show()
```



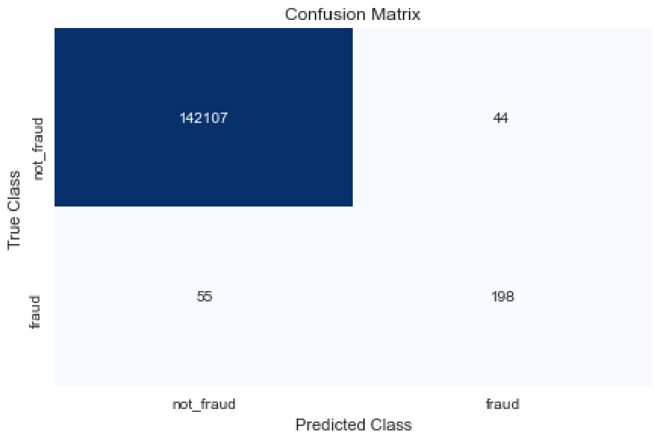
Precision&Recall

In [177]:

```
#confusion matrix
class_names = ['not_fraud', 'fraud']
matrix_svm = confusion_matrix(Ytest, preds_svm)

precision_svm = [matrix_svm[0][0]/(matrix_svm[0][0]+matrix_svm[1][0]),
             matrix_svm[1][1]/(matrix_svm[1][1]+matrix_svm[0][1])]
recall_svm = [matrix_svm[0][0]/(matrix_svm[0][0]+matrix_svm[0][1]),
          matrix_svm[1][1]/(matrix_svm[1][1]+matrix_svm[1][0])]

acc_svm =(matrix_svm[0][0]+matrix_svm[1][1])/(sum(matrix_svm[0]) + sum(matrix_svm[1]))
```

In [178]:

```
# Create pandas dataframe
dataframe = pd.DataFrame(matrix_svm, index=class_names, columns=class_names)
# Create heatmap
sns.heatmap(dataframe, annot=True, cbar=None, cmap="Blues", fmt = 'g')
plt.title("Confusion Matrix"), plt.tight_layout()
plt.ylabel("True Class"), plt.xlabel("Predicted Class")
plt.show()
```



In [179]:

```
#print
print('We have detected ' + str(matrix_svm[1][1]) + ' frauds / ' +
      str(matrix_svm[1][1]+matrix_svm[1][0]) + ' total frauds.')
print('\nSo, the probability to detect a fraud is ' +
      str(matrix_svm[1][1]/(matrix_svm[1][1]+matrix_svm[1][0])))
print("the accuracy is : "+ str(acc_svm))

print(f'SVM (C=5) model accuracy is {str(acc_svm)}')
print(f'SVM (C=5) model precision for 0 and 1 is {precision_svm}')
print (f'SVM (C=5) model recall for 0 and 1  is {recall_svm}')
```

```
We have detected 198 frauds / 253 total frauds.

So, the probability to detect a fraud is 0.782608695652174
the accuracy is : 0.9993047948091346
SVM (C=5) model accuracy is 0.9993047948091346
SVM (C=5) model precision for 0 and 1 is [0.9996131174294115, 0.8181818181818182]
SVM (C=5) model recall for 0 and 1  is [0.9996904699931762, 0.782608695652174]
```

Conclusion---Best SVM Model

In [180]:

```
svm_model = pd.DataFrame({
    'Model': ['Support Vector Machine'],
    'AUC Score': [auc_svm],
    'Recall': [recall_svm[1]],
    'Precision': [precision_svm[1]],
    'Accuracy': [acc_svm]
})

display(svm_model)
```

	Model	AUC Score	Recall	Precision	Accuracy
0	Support Vector Machine	0.93085	0.782609	0.818182	0.999305

6. Random Forest

6.1 Models with different number of estimators

In [194]:

```
n_estimators = [1000, 1200, 1500, 2000, 2500, 5000]
frame = pd.DataFrame(columns = ['n_est', 'max_depth', 'AUC'])

for est in n_estimators:
    rfc = RandomForestClassifier(max_depth = None, n_estimators = est )
    rfc.fit(Xtrain, Ytrain)

    rfcfpr1 = dict()
    rfctpr1 = dict()
    lw = 2
    #predictions
    rfc_score = rfc.predict_proba(Xval)[:,1]
    rfcfpr1 = roc_curve(Yval, rfc_score)[0]
    rfctpr1 = roc_curve(Yval, rfc_score)[1]
    rfc_auc = roc_auc_score(Yval, rfc_score)

    frame = frame.append({'n_est' : est, 'max_depth' : None, 'AUC' : rfc_auc},
            ignore_index = True)
    print("Done with: {}, None".format(est))

display(frame)
```

```
Done with: 1000, None
Done with: 1200, None
Done with: 1500, None
Done with: 2000, None
Done with: 2500, None
Done with: 5000, None
```

	n_est	max_depth	AUC
0	1000.0	NaN	0.973516
1	1200.0	NaN	0.974837
2	1500.0	NaN	0.974434
3	2000.0	NaN	0.984181
4	2500.0	NaN	0.983707
5	5000.0	NaN	0.983510

Analysis: On testing Sample

In [195]:

```
#So we choose n=2000, random forest model creation
rfc = RandomForestClassifier(max_depth = None, n_estimators = 2000)
rfc.fit(Xtrain, Ytrain)
```

```
RandomForestClassifier(n_estimators=2000)
```

In [196]:

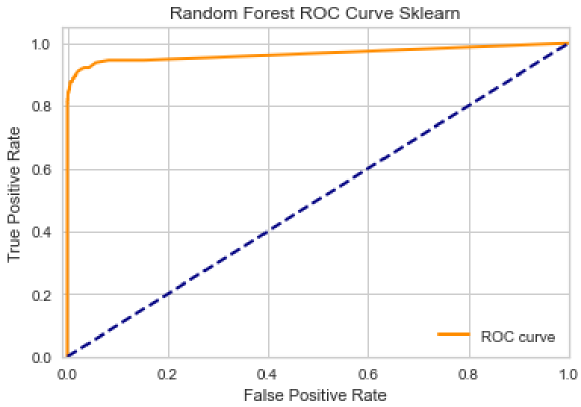
```
#predictions
pred_rfc = rfc.predict(Xtest)
#auc predictions
score_rfc = rfc.predict_proba(Xtest)[:,1]
```

AUC Score

In [197]:

```
#AUC CURVE
fpr, tpr, thresholds = roc_curve(Ytest, score_rfc)
auc_rfc = metrics.auc(fpr, tpr)
print('Random Forest AUC for testing sample: {}'.format(auc_rfc))

plt.figure()
lw = 2
plt.plot(fpr, tpr, color='darkorange',
         lw=lw, label='ROC curve')
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([-0.01, 1.0])
plt.ylim([0.0, 1.05])

plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Random Forest ROC Curve Sklearn')
plt.legend(loc="lower right")
plt.show()
```

```
Random Forest AUC for testing sample: 0.965758048357l4
```



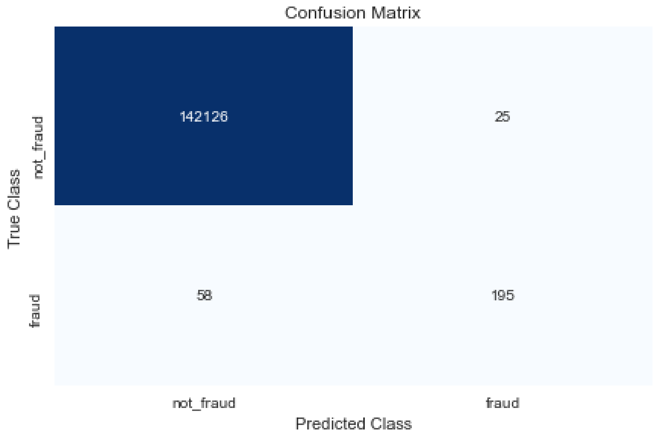
Precision&Recall

In [198]:

```
#confusion matrix
class_names = ['not_fraud', 'fraud']
rfcmatrix = confusion_matrix(Ytest,pred_rfc)
rfcprecision = [rfcmatrix[0][0]/(rfcmatrix[0][0]+rfcmatrix[1][0]),
                rfcmatrix[1][1]/(rfcmatrix[1][1]+rfcmatrix[0][1])]
rfcrecall = [rfcmatrix[0][0]/(rfcmatrix[0][0]+rfcmatrix[0][1]),
             rfcmatrix[1][1]/(rfcmatrix[1][1]+rfcmatrix[1][0])]
rfcacc = (rfcmatrix[0][0]+rfcmatrix[1][1]) / (sum(rfcmatrix[0]) + sum(rfcmatrix[1]))
```

In [199]:

```
# Create pandas dataframe
rfcdataframe = pd.DataFrame(rfcmatrix, index=class_names, columns=class_names)
# Create heatmap
sns.heatmap(rfcdataframe, annot=True, cbar=None, cmap="Blues", fmt = 'g')
plt.title("Confusion Matrix"), plt.tight_layout()
plt.ylabel("True Class"), plt.xlabel("Predicted Class")
plt.show()
```



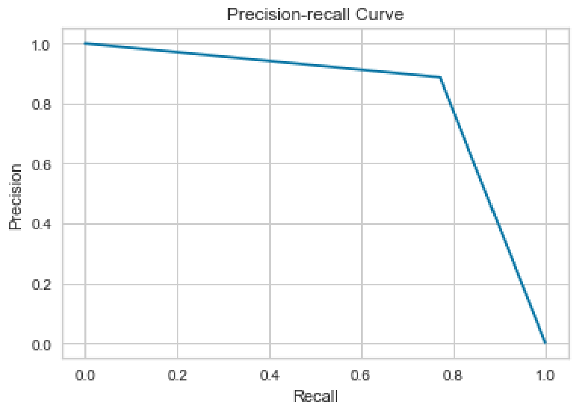
In [200]:

```
#print
print('We have detected ' + str(rfcmatrix[1][1]) + ' frauds / ' +
      str(rfcmatrix[1][1]+rfcmatrix[1][0]) + ' total frauds.')
print('\nSo, the probability to detect a fraud is ' +
      str(rfcmatrix[1][1]/(rfcmatrix[1][1]+rfcmatrix[1][0])))
print("the accuracy is : "+ str(rfcacc ))

print(f'Random Forest model accuracy is {rfcacc}')
print(f'Random Forest model precision for 0 and 1 is {rfcprecision}')
print (f'Random Forest model recall for 0 and 1  is {rfcrecall}')
```

```
We have detected 195 frauds / 253 total frauds.

So, the probability to detect a fraud is 0.7707509881422925
the accuracy is : 0.9994171512036178
Random Forest model accuracy is 0.9994171512036178
Random Forest model precision for 0 and 1 is [0.9995920778709279, 0.8863636363636364]
Random Forest model recall for 0 and 1  is [0.9998241306779411, 0.7707509881422925]
```

In [201]:
```
#Precision Recall Curve
precisionp, recallp, _ = precision_recall_curve(Ytest, pred_rfc)
plt.plot(recallp, precisionp)

plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("Precision-recall Curve")
plt.legend(loc="lower right")
plt.show()
```

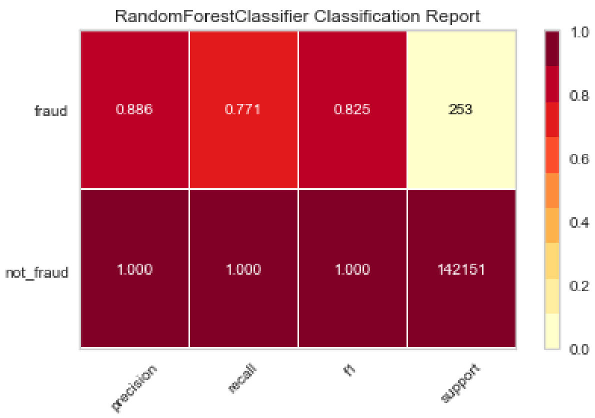
```
No handles with labels found to put in legend.
```



In [202]:
```
#need more decimals
print(classification_report(Ytest, pred_rfc))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00    142151
           1       0.89      0.77      0.82       253

    accuracy                           1.00    142404
   macro avg       0.94      0.89      0.91    142404
weighted avg       1.00      1.00      1.00    142404
```

In [206]:
```
visualizer = ClassificationReport(rfc, classes = class_names, support = True)
visualizer.fit( Xtrain, Ytrain)        # Fit the visualizer and the model
visualizer.score(Xtest, Ytest)        # Evaluate the model on the test data
visualizer.show()
```




```
<matplotlib.axes._subplots.AxesSubplot at 0x1d9b3cc5f40>
```

In [203]:
```
# evaluation
# calculate average error and standard deviation
testYDiff = np.abs(Ytest-pred_rfc)
avgErr_rfc = np.mean(testYDiff)
stdErr_rfc = np.std(testYDiff)

print('Random Forest average error: {} ({})'.format(avgErr_rfc, stdErr_rfc))
```

```
Random Forest average error: 0.000582848796382124 (0.024135224955709026)
```

Conclusion---Best Random Forest Model

In [204]:
```
rfc_model = pd.DataFrame({
    'Model': ['Random Forest'],
    'AUC Score': [auc_rfc],
    'Recall': [rfcrecall[1]],
    'Precision': [rfcprecision[1]],
    'Accuracy': [rfcacc]
})

display(rfc_model)
```

	Model	AUC Score	Recall	Precision	Accuracy
0	Random Forest	0.965758	0.770751	0.886364	0.999417

Model Comparison

In [60]:
```
models_best = pd.DataFrame()

models_best = models_best.append([linear_model, logit_model, knn_model,
                                  fnn_model, svm_model, rfc_model],
                                 ignore_index=True)

display(models_best)

#models_best.to_csv("model.csv")
```

	Model	AUC Score	Recall	Precision	Accuracy
0	LinearDiscriminantAnalysis	0.983247	0.770751	0.855263	0.999361
1	Logistic Regression - Lasso Penalization 2	0.812179	0.624506	0.882682	0.999185
2	KNearestNeighbors Model	0.912884	0.766798	0.873874	0.999389
3	FNN Model 1	0.893119	0.786561	0.812245	0.999298
4	Support Vector Machine	0.930850	0.782609	0.818182	0.999305
5	Random Forest	0.965758	0.770751	0.886364	0.999417