APS Component failure prediction

1. Business Problem

1.1. Description

Data Source: https://ida2016.blogs.dsv.su.se/?page_id=1387

Data: Scania Trucks

Problem statement :

The system in focus is the Air Pressure system (APS) which generates pressurized air that are utilized in various functions in a truck, such as braking and gear changes. The datasets positive class corresponds to component failures for a specific component of the APS system. The negative class corresponds to trucks with failures for components not related to the APS system.

The prbolem is to reduce the cost due to unecessary repairs. So it is required to minimize the false predictions.

Predicted class | True class | | pos | neg |

```
pos      |           | cost_1 |
```

```
neg      | cost_2    |        |
```

Cost_1 = 10 and cost_2 = 500

The total cost of a prediction model the sum of "Cost_1" multiplied by the number of Instances with type 1 failure and "Cost_2" with the number of instances with type 2 failure, resulting in a "Total_cost". In this case Cost_1 refers to the cost that an unnessecary check needs to be done by an mechanic at an workshop, while Cost_2 refer to the cost of missing a faulty truck, which may cause a breakdown. Total_cost = Cost_1 * No_Instances + Cost_2 * No_Instances.

- from the above problem statement we could observe that, we have to reduce false positives and false negatives.
- More importantly we have to reduce false negatives, since cost incurred due to false negative is 50 times higher than the false positives.

1.2. Key performance metric

- Here we have to reduce False Negative and False Positive, so clearly we can use precision and recall as performance metric.

- But here is a simpler metric which takes into account both precision and recall, and therefore, we can aim to maximize this number to make your model better. This metric is known as F1-score, which is simply the harmonic mean of precision and recall.

Generally f1 score balance the precision and recall but one simple idea is that, because of cost incurred due to false negative is 50 times higher than the false positives, for this specific problem if we could try to slightly increase recall we may get better results .

we should decrease false negatives in such a way that one point decrease in FN can be accepted for the cost of 49 FP. Since 1 point cost of FN = 50 point cost of FP

1.3. Real-world/Business objectives and constraints.

- No low-latency requirement.
- Interpretability is not important.
- misclassification leads the unecessary repair costs.

2. Machine Learning Problem Formulation

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings("ignore")
from sklearn.impute import SimpleImputer
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
from sklearn.metrics import precision_recall_curve, auc, roc_curve
import seaborn as sns
from sklearn.metrics import f1_score
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import precision_recall_curve
from sklearn.decomposition import PCA
import missingno as msno
from sklearn.preprocessing import StandardScaler
from xgboost import XGBClassifier
from sklearn.linear_model import SGDClassifier
from imblearn.over_sampling import SMOTE
from sklearn.calibration import CalibratedClassifierCV
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
warnings.filterwarnings("ignore")
```

Data Loading and preprocessing

In [2]:

```
train = pd.read_csv("aps_failure_training_set.csv")
test = pd.read_csv("aps_failure_test_set.csv")
```

In [3]:

```
train.head()
```

Out[3]:

	class	aa_000	ab_000	ac_000	ad_000	ae_000	af_000	ag_000	ag_001	ag_002	...	ee_002	ee_003	ee_004	ee_00
0	neg	76698	na	2130706438	280	0	0	0	0	0	...	1240520	493384	721044	46979
1	neg	33058	na	0	na	0	0	0	0	0	...	421400	178064	293306	24541
2	neg	41040	na	228	100	0	0	0	0	0	...	277378	159812	423992	40956
3	neg	12	0	70	66	0	10	0	0	0	...	240	46	58	44
4	neg	60874	na	1368	458	0	0	0	0	0	...	622012	229790	405298	34718

5 rows × 171 columns

In [4]:

```
test.head()
```

Out[4]:

	class	aa_000	ab_000	ac_000	ad_000	ae_000	af_000	ag_000	ag_001	ag_002	...	ee_002	ee_003	ee_004	ee_005	ee

0	class	aa_000	ab_000	ac_000	ad_000	ae_000	af_000	ag_000	ag_001	ag_002	...	ee_002	ee_003	ee_004	ee_005	ee
0	neg	60	0	20	12	0	0	0	0	0	...	1098	138	412	654	78
1	neg	82	0	68	40	0	0	0	0	0	...	1068	276	1620	116	86
2	neg	66002	2	212	112	0	0	0	0	0	...	495076	380368	440134	269556	131
3	neg	59816	na	1010	936	0	0	0	0	0	...	540820	243270	483302	485332	431
4	neg	1814	na	156	140	0	0	0	0	0	...	7646	4144	18466	49782	317

5 rows × 171 columns

In [5]:

```
print("shape of train dataset:",train.shape)
print("shape of test dataset:",test.shape)
```

```
shape of train dataset: (60000, 171)
shape of test dataset: (16000, 171)
```

In [6]:

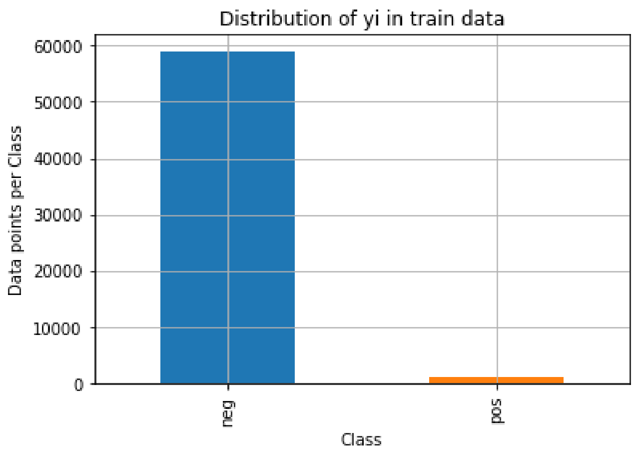
```
train["class"].unique()
```

Out[6]:

```
array(['neg', 'pos'], dtype=object)
```

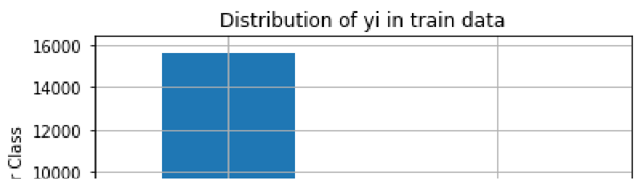
In [7]:

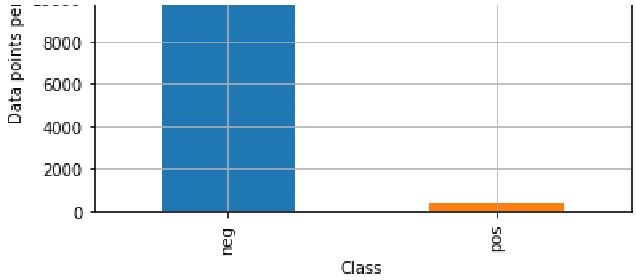
```
train_class_distribution = train['class'].value_counts()
train_class_distribution.plot(kind='bar')
plt.xlabel('Class')
plt.ylabel('Data points per Class')
plt.title('Distribution of yi in train data')
plt.grid()
plt.show()
```



In [8]:

```
train_class_distribution = test['class'].value_counts()
train_class_distribution.plot(kind='bar')
plt.xlabel('Class')
plt.ylabel('Data points per Class')
plt.title('Distribution of yi in train data')
plt.grid()
plt.show()
```





Observation:

- from above Bar Plots, we could conclude that the given data is highly imbalanced

In [9]:

```
train.replace(to_replace = 'neg', value = 0, inplace = True)
train.replace(to_replace = 'pos', value = 1, inplace = True)
test.replace(to_replace = 'neg', value = 0, inplace = True)
test.replace(to_replace = 'pos', value = 1, inplace = True)
```

In [10]:

```
y_train = train["class"]
train.drop(['class'],axis = 1,inplace = True)
y_test = test["class"]
test.drop(['class'],axis = 1,inplace = True)
```

Checking for Missing Values

In [11]:

```
# In the given data missing values are represented as "na", but we require in the
# np.NaN format to process the data

train.replace(to_replace = 'na', value = np.NaN, inplace = True)
test.replace(to_replace = 'na', value = np.NaN, inplace = True)
```

In [12]:

```
train.head()
```

Out[12]:

	aa_000	ab_000	ac_000	ad_000	ae_000	af_000	ag_000	ag_001	ag_002	ag_003	...	ee_002	ee_003	ee_004	ee_(
0	76698	NaN	2130706438	280	0	0	0	0	0	0	...	1240520	493384	721044	4697
1	33058	NaN	0	NaN	0	0	0	0	0	0	...	421400	178064	293306	2454
2	41040	NaN	228	100	0	0	0	0	0	0	...	277378	159812	423992	4095
3	12	0	70	66	0	10	0	0	0	318	...	240	46	58	44
4	60874	NaN	1368	458	0	0	0	0	0	0	...	622012	229790	405298	3471

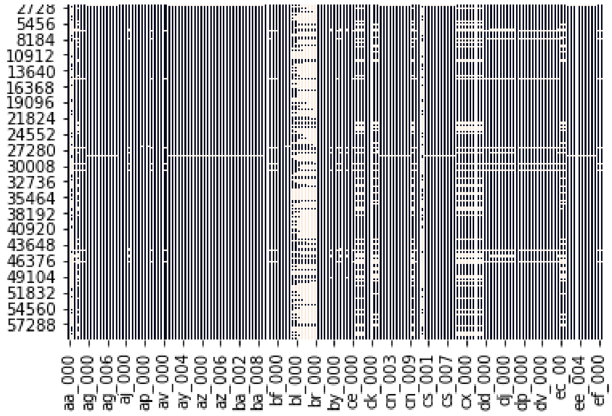
5 rows × 170 columns

In [13]:

```
#https://dev.to/tomoyukiaota/visualizing-the-patterns-of-missing-value-occurrence-with-python-46dj
sns.heatmap(train.isnull(), cbar=False)
```

Out[13]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x18106dac9b0>
```

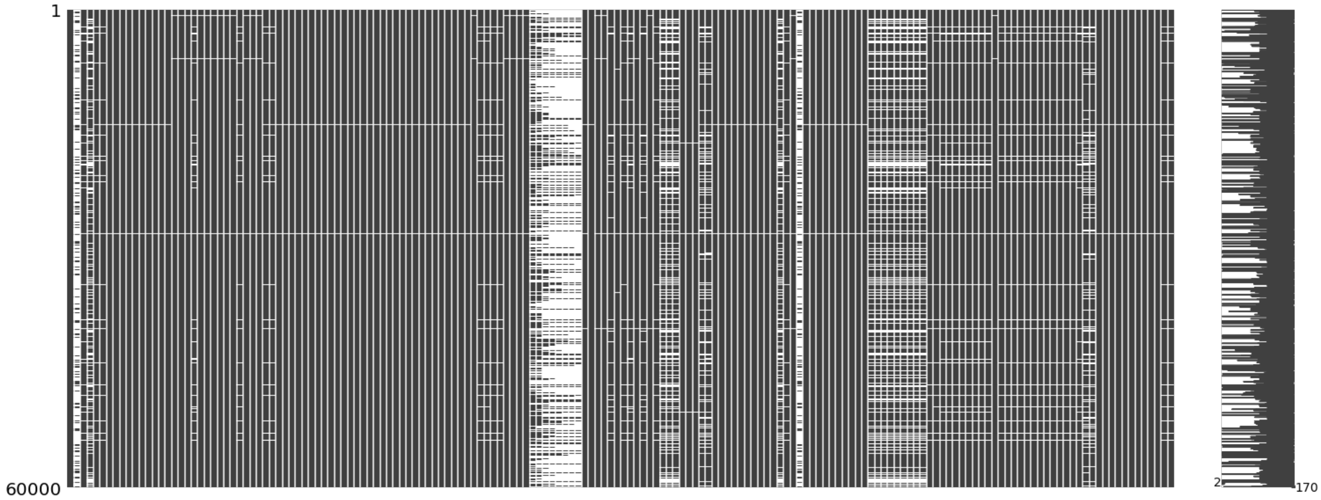


In [14]:

```
msno.matrix(train)
```

Out[14]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x18106de1748>
```



Oservations:

- There are lot of missing values in the data, so we cannot remove the rows as it will leads to the great amount of information loss.
- To avoid the information loss we will implement below two ideas to deal with the missing values.
    - Remove columns which contains more than 75% of NaN values.
    - Imputation techniques

In [15]:

```
# 75% of 60000 = 45000
train.dropna(axis = 1, thresh=45000,inplace= True)
```

In [16]:

```
new_columns = train.columns
```

In [17]:

```
# Finding removed columns
removed_columns = []
for i in test.columns:
    if i not in new_columns:
        removed_columns.append(i)
```

In [18]:

```
# Dropping removed columns of train data from test data
```

```
# Dropping removed columns of train data from test data
test.drop(removed_columns,axis = 1,inplace = True)
```

In [19]:

```
test.shape
```

Out[19]:

```
(16000, 160)
```

Imputation Techniques

- popular Imputation Techniques are:
  - Mean Imputation
  - Median Imputation
  - constant value imputation
  - Most_frequent value imputation
- Most_frequent value imputation will work fairly well on categorical data. Since our data is continuous we will focus on first 3 methods.

Mean Imputation

In [20]:

```
mean_imputation = SimpleImputer(missing_values= np.nan , strategy="mean")
x_train_mean = mean_imputation.fit_transform(train)
x_test_mean = mean_imputation.transform(test)
```

Median Imputation

In [21]:

```
median_imputation = SimpleImputer(missing_values= np.nan , strategy="median")
x_train_median = median_imputation.fit_transform(train)
x_test_median = median_imputation.transform(test)
```

constant value imputation

In [22]:

```
constant_imputation = SimpleImputer(missing_values= np.nan,strategy='constant', fill_value=-1)
x_train_constant = constant_imputation.fit_transform(train)
x_test_constant = constant_imputation.transform(test)
```

Balancing the data using SMOTE(Synthetic Minority Oversampling Technique)

- SMOTE is an oversampling method. It works by creating synthetic samples from the minor class instead of creating copies. The algorithm selects two or more similar instances (using a distance measure) and perturbing an instance one attribute at a time by a random amount within the difference to the neighboring instances.

SMOTE for mean Imputed data

In [23]:

```
sm = SMOTE(random_state=2)
X_train_mean_sm, y_train_mean = sm.fit_sample(x_train_mean, y_train.ravel())
```

In [24]:

```
from sklearn.preprocessing import StandardScaler
```

In [25]:

```
# Standardizing the data
ss = StandardScaler()
X_train_mean_std = ss.fit_transform(X_train_mean_sm)
X_test_mean_std = ss.transform(x_test_mean)
```

SMOTE for median Imputed data

In [26]:

```
sm = SMOTE(random_state=2)
X_train_median_sm, y_train_median = sm.fit_sample(x_train_median, y_train.ravel())
```

In [27]:

```
ss = StandardScaler()
X_train_median_std = ss.fit_transform(X_train_median_sm)
X_test_median_std = ss.transform(x_test_median)
```

SMOTE for constant value Imputed data

In [28]:

```
sm = SMOTE(random_state=2)
X_train_con_sm, y_train_constant = sm.fit_sample(x_train_constant, y_train.ravel())
```

In [29]:

```
ss = StandardScaler()
X_train_constant_std = ss.fit_transform(X_train_con_sm)
X_test_constant_std = ss.transform(x_test_constant)
```

Utility Functions

In [30]:

```
def plot_confusion_matrix(test_y, predict_y):

    '''
    This function takes y_ture, y_predicted, and prints consfusion matrix,
    f1_score and Total cost due to misclassification

    '''
    C = confusion_matrix(test_y, predict_y)

    plt.figure(figsize=(8,4))

    labels = ["neg","pos"]
    # representing A in heatmap format
    cmap=sns.light_palette("blue")
    sns.heatmap(C, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Confusion matrix")

    plt.show()
    cost_1 = 10*C[0][1]
    cost_2 = 500*C[1][0]
    total_cost = cost_1 + cost_2
    print("f1_score :",f1_score(test_y, predict_y))
    print("Total Cost due to mis classifiation:",total_cost)
```

In [31]:

In [31]:

```python
def total_cost(test_y, predict_y):
    '''
    This function takes y_ture, y_predicted, and prints Total cost due to misclassification

    '''
    C = confusion_matrix(test_y, predict_y)
    cost_1 = 10*C[0][1]
    cost_2 = 500*C[1][0]
    total = (cost_1 + cost_2)
    return total
```

In [32]:

```python
#https://towardsdatascience.com/fine-tuning-a-classifier-in-scikit-learn-66e048c21e65
def plot_precision_recall_vs_threshold(precisions, recalls, thresholds):
    """
        Gives the plot of precision and recall vs thresholds
    """
    plt.figure(figsize=(8, 8))
    plt.title("Precision and Recall Scores as a function of the decision threshold")
    plt.plot(thresholds, precisions[:-1], "b--", label="Precision")
    plt.plot(thresholds, recalls[:-1], "g-", label="Recall")
    plt.ylabel("Score")
    plt.xlabel("Decision Threshold")
    plt.legend(loc='best')
    plt.grid()
    plt.show()
```

In [59]:

```python
def pred_with_threshold(sig_clf_probs,t):
    '''
    This function takes proability scores and threshold value and classifies predictions based on
threshold value

    '''


    predictions = []
    for i in sig_clf_probs:
        if i>=t:
            predictions.append(1)
        else:
            predictions.append(0)
    return predictions
```

Random Model

In [34]:

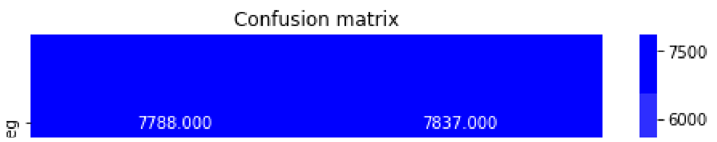
```python
import random
```

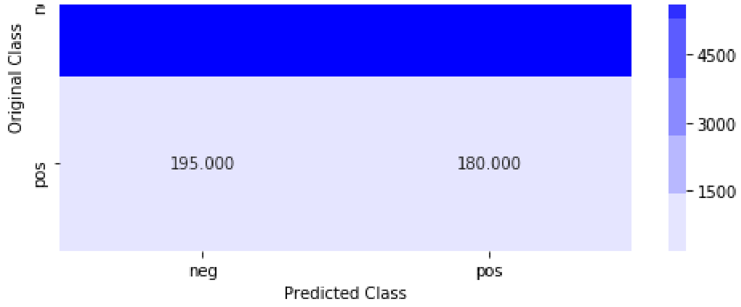
In [35]:

```python
test_len = X_test_mean_std.shape[0]
predicted_y = np.zeros((test_len))
for i in range(test_len):
    predicted_y[i] =random.randint(0,1)
print("f1_score on Test Data using Random Model",f1_score(y_test, predicted_y))

plot_confusion_matrix(y_test, predicted_y)
```

```
f1_score on Test Data using Random Model 0.04289799809342231
```






```
f1_score : 0.04289799809342231
Total Cost due to mis classifiation: 175870
```

- with simple Random model we got f1_score as 0.047 and cost as 1,71,090. This would be the benchmark for our models

4.3. svm with mean

In [ ]:

```
parameters = {"C": [10 ** x for x in range(-6, 3)]}

#Gridsearch CV with 8 fold crossvalidation

svc = SVC()
GCV = GridSearchCV(svc,param_grid=parameters, scoring = "f1", verbose = 1,cv=8, n_jobs = -1)
GCV.fit(X_train_mean_std , y_train_mean )
```

```
Fitting 8 folds for each of 9 candidates, totalling 72 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
```

In [63]:

```
clf= GCV.best_estimator_
```

In [64]:

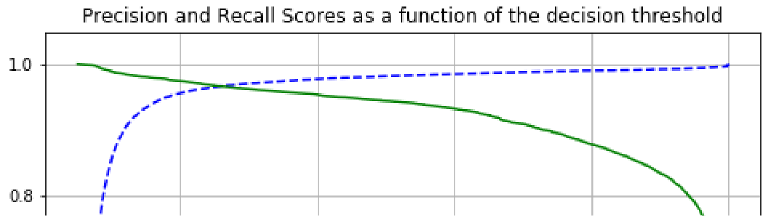
```
GCV.best_estimator_
```

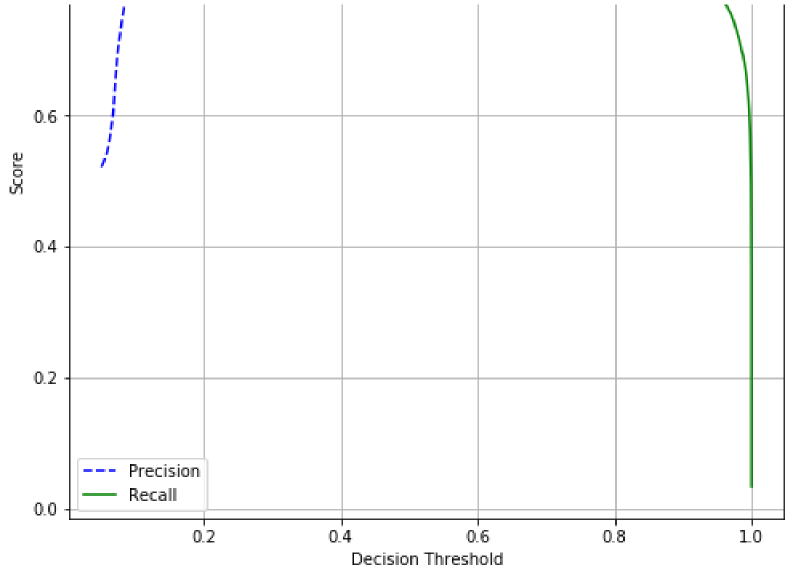
Out[64]:

```
SGDClassifier(alpha=0.001, average=False, class_weight=None,
       early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True,
       l1_ratio=0.15, learning_rate='optimal', loss='hinge', max_iter=None,
       n_iter=None, n_iter_no_change=5, n_jobs=None, penalty='l2',
       power_t=0.5, random_state=None, shuffle=True, tol=None,
       validation_fraction=0.1, verbose=0, warm_start=False)
```

In [68]:

```
x_t, x_c, y_t, y_c = train_test_split(X_train_mean_std , y_train_mean, stratify=y_train_mean, test_
size=0.3)
clf.fit(x_t, y_t)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(x_t, y_t)
sig_clf_probs = sig_clf.predict_proba(x_c)[:,1]
presicision, recall, tresholds =precision_recall_curve(y_c,sig_clf_probs)
plot_precision_recall_vs_threshold(presicision, recall, tresholds)
```





In [69]:

```
t=0.25
```

In [70]:

```
clf= GCV.best_estimator_
clf.fit(X_train_mean_std , y_train_mean)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(X_train_mean_std , y_train_mean)
test_clf_probs = sig_clf.predict_proba(X_test_mean_std)[:,1]
train_clf_probs = sig_clf.predict_proba(X_train_mean_std)[:,1]
```

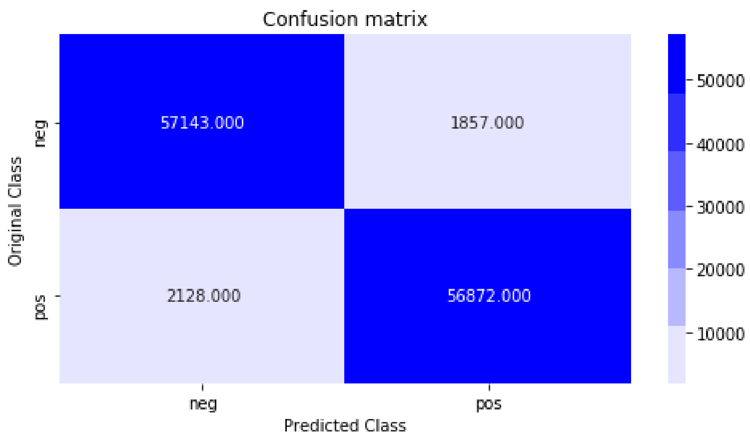
In [71]:

```
train_predictions = pred_with_threshold(train_clf_probs,t)
test_predictions = pred_with_threshold(test_clf_probs,t)
```

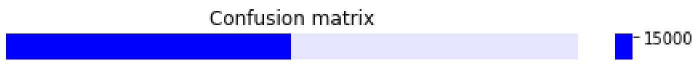
In [72]:

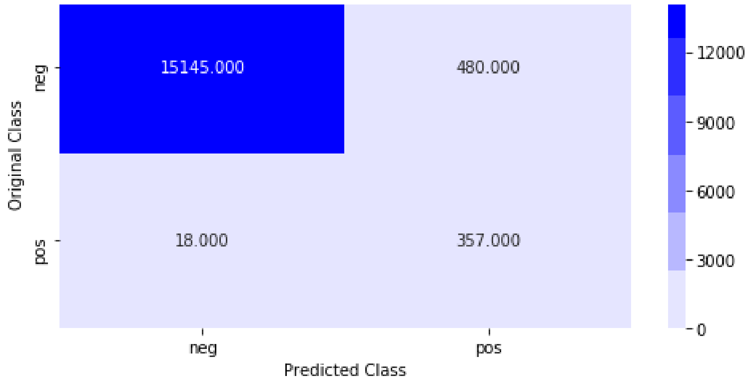
```
print("Train Confusion Matrix")
plot_confusion_matrix(y_train_mean, train_predictions)
print("Test Confusion Matrix")
plot_confusion_matrix(y_test, test_predictions)
```

```
Train Confusion Matrix
```




```
f1_score : 0.9661510757757221
Total Cost due to mis classifiation: 1082570
Test Confusion Matrix
```






```
f1_score : 0.5891089108910891
Total Cost due to mis classifiation: 13800
```

4.3. Linear\logistic Regression with mean

In [62]:

```
parameters = {"alpha": [10 ** x for x in range(-6, 3)], "penalty" : ['l2','l1'], "loss" : ['log','h
inge']}

#Gridsearch CV with 8 fold crossvalidation

LR = SGDClassifier()
GCV = GridSearchCV(LR,param_grid=parameters, scoring = "f1", verbose = 1,cv=8, n_jobs = -1)
GCV.fit(X_train_mean_std , y_train_mean )
```

```
Fitting 8 folds for each of 36 candidates, totalling 288 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  42 tasks      | elapsed:   34.4s
[Parallel(n_jobs=-1)]: Done 192 tasks      | elapsed:  2.1min
[Parallel(n_jobs=-1)]: Done 288 out of 288 | elapsed:  3.2min finished
```

Out[62]:

```
GridSearchCV(cv=8, error_score='raise-deprecating',
       estimator=SGDClassifier(alpha=0.0001, average=False, class_weight=None,
       early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True,
       l1_ratio=0.15, learning_rate='optimal', loss='hinge', max_iter=None,
       n_iter=None, n_iter_no_change=5, n_jobs=None, penalty='l2',
       power_t=0.5, random_state=None, shuffle=True, tol=None,
       validation_fraction=0.1, verbose=0, warm_start=False),
       fit_params=None, iid='warn', n_jobs=-1,
       param_grid={'alpha': [1e-06, 1e-05, 0.0001, 0.001, 0.01, 0.1, 1, 10, 100], 'penalty':
['l2', 'l1'], 'loss': ['log', 'hinge']},
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='f1', verbose=1)
```

In [63]:

```
clf= GCV.best_estimator_
```

In [64]:

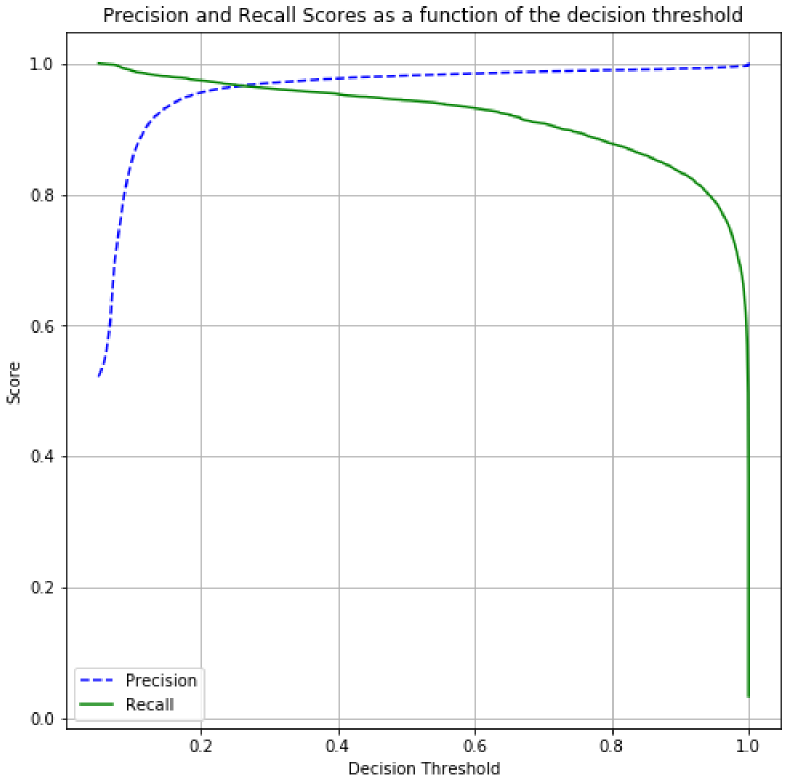
```
GCV.best_estimator_
```

Out[64]:

```
SGDClassifier(alpha=0.001, average=False, class_weight=None,
       early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True,
       l1_ratio=0.15, learning_rate='optimal', loss='hinge', max_iter=None,
       n_iter=None, n_iter_no_change=5, n_jobs=None, penalty='l2',
       power_t=0.5, random_state=None, shuffle=True, tol=None,
       validation_fraction=0.1, verbose=0, warm_start=False)
```

In [68]:

```
x_t, x_c, y_t, y_c = train_test_split(X_train_mean_std , y_train_mean, stratify=y_train_mean, test_
size=0.3)
clf.fit(x_t, y_t)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(x_t, y_t)
sig_clf_probs = sig_clf.predict_proba(x_c)[:,1]
presicision, recall, tresholds =precision_recall_curve(y_c,sig_clf_probs)
plot_precision_recall_vs_threshold(presicision, recall, tresholds)
```



In [69]:

```
t=0.25
```

In [70]:

```
clf= GCV.best_estimator_
clf.fit(X_train_mean_std , y_train_mean)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(X_train_mean_std , y_train_mean)
test_clf_probs = sig_clf.predict_proba(X_test_mean_std)[:,1]
train_clf_probs = sig_clf.predict_proba(X_train_mean_std)[:,1]
```

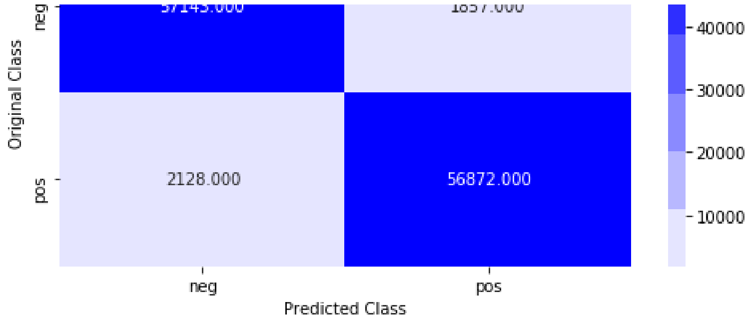
In [71]:

```
train_predictions = pred_with_threshold(train_clf_probs,t)
test_predictions = pred_with_threshold(test_clf_probs,t)
```

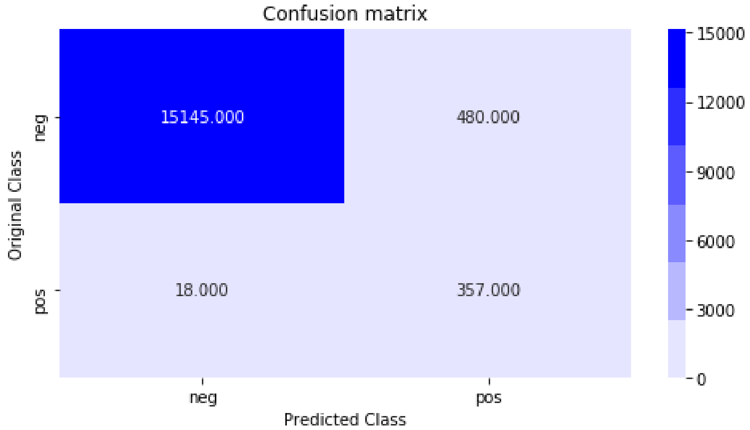
In [72]:

```
print("Train Confusion Matrix")
plot_confusion_matrix(y_train_mean, train_predictions)
print("Test Confusion Matrix")
plot_confusion_matrix(y_test, test_predictions)
```

Train Confusion Matrix




```
f1_score : 0.9661510757757221
Total Cost due to mis classifiation: 1082570
Test Confusion Matrix
```




```
f1_score : 0.5891089108910891
Total Cost due to mis classifiation: 13800
```

XGB with mean

In [38]:

```
parameters = {"max_depth": [5,8,10] , "n_estimators":[300,500,1000,2000]}


#Gridsearch CV with 2 fold crossvalidation

xgb = XGBClassifier()
GCV = GridSearchCV(xgb,param_grid=parameters, scoring = "f1", verbose = 1,cv=2, n_jobs = -1)
GCV.fit(X_train_mean_std , y_train_mean)
```

```
Fitting 2 folds for each of 12 candidates, totalling 24 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  24 out of  24 | elapsed: 128.1min finished
```

Out[38]:

```
GridSearchCV(cv=2, error_score='raise-deprecating',
             estimator=XGBClassifier(base_score=0.5, booster='gbtree',
                                     colsample_bylevel=1, colsample_bynode=1,
                                     colsample_bytree=1, gamma=0,
                                     learning_rate=0.1, max_delta_step=0,
                                     max_depth=3, min_child_weight=1,
                                     missing=None, n_estimators=100, n_jobs=1,
                                     nthread=None, objective='binary:logistic',
                                     random_state=0, reg_alpha=0, reg_lambda=1,
                                     scale_pos_weight=1, seed=None, silent=None,
                                     subsample=1, verbosity=1),
             iid='warn', n_jobs=-1,
             param_grid={'max_depth': [5, 8, 10],
                         'n_estimators': [300, 500, 1000, 2000]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring='f1', verbose=1)
```

In [39]:

```
clf_xgb_mean= GCV.best_estimator_
```

In [40]:

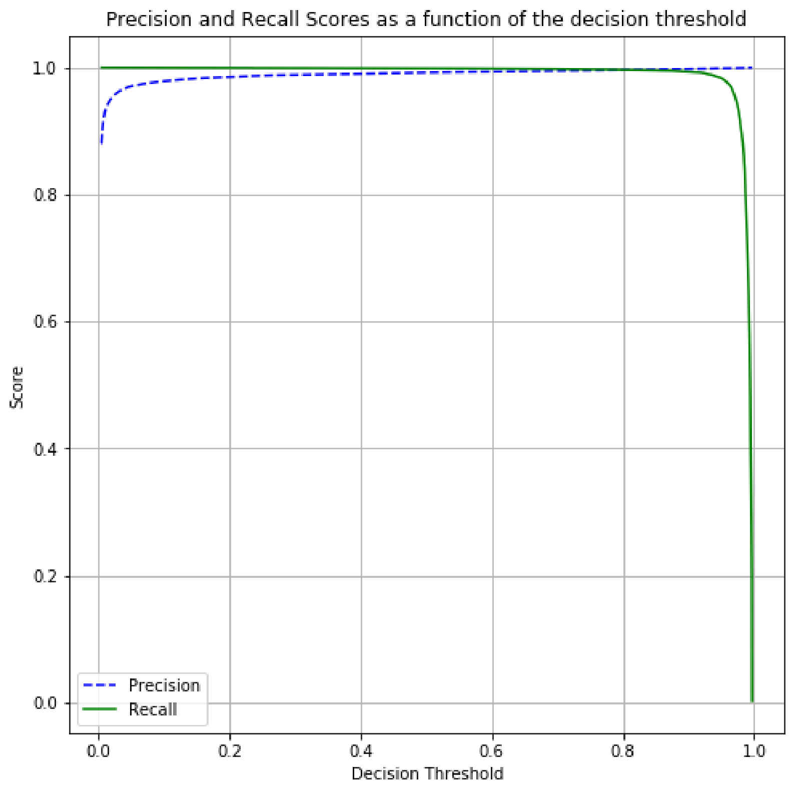
```
GCV.best_estimator_
```

Out[40]:

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0,
              learning_rate=0.1, max_delta_step=0, max_depth=10,
              min_child_weight=1, missing=None, n_estimators=300, n_jobs=1,
              nthread=None, objective='binary:logistic', random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
              silent=None, subsample=1, verbosity=1)
```

In [42]:

```
x_t, x_c, y_t, y_c = train_test_split(X_train_mean_std, y_train_mean, stratify=y_train_mean, test_s
ize=0.3)
clf_xgb_mean.fit(x_t, y_t)
sig_clf_probs = clf_xgb_mean.predict_proba(x_c)[:,1]
#train_predict = clf.predict(x_train)
#cross_predict = clf.predict(x_test)
presicision, recall, tresholds =precision_recall_curve(y_c,sig_clf_probs)
plot_precision_recall_vs_threshold(presicision, recall, tresholds)
```



In [45]:

```
t=0.8
```

In [44]:

```
clf= GCV.best_estimator_
clf.fit(X_train_mean_std , y_train_mean)
```

Out[44]:

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
```

```
colsample_bynode=1, colsample_bytree=1, gamma=0,
learning_rate=0.1, max_delta_step=0, max_depth=10,
min_child_weight=1, missing=None, n_estimators=300, n_jobs=1,
nthread=None, objective='binary:logistic', random_state=0,
reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
silent=None, subsample=1, verbosity=1)
```

In [46]:

```
test_clf_probs = clf.predict_proba(X_test_mean_std)[:,1]
train_clf_probs = clf.predict_proba(X_train_mean_std)[:,1]
```

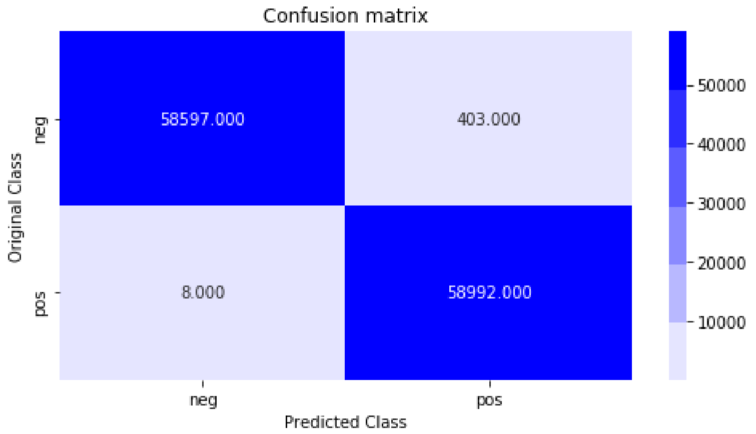
In [47]:

```
train_predictions = pred_with_threshold(train_clf_probs,t)
test_predictions = pred_with_threshold(test_clf_probs,t)
```

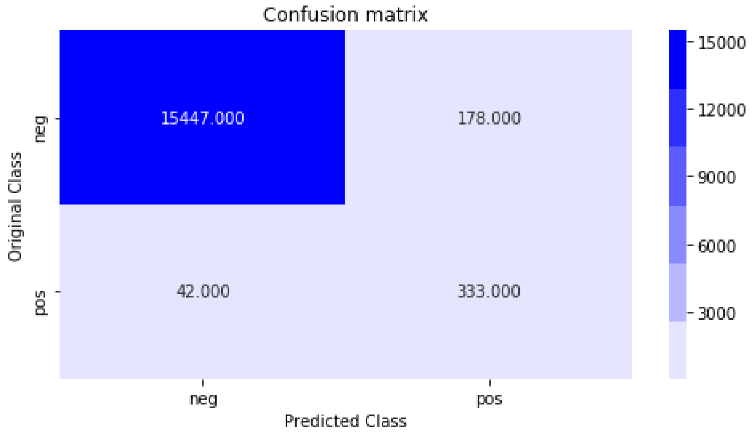
In [48]:

```
print("Train Confusion Matrix")
plot_confusion_matrix(y_train_constant, train_predictions)
print("Test Confusion Matrix")
plot_confusion_matrix(y_test, test_predictions)
```

```
Train Confusion Matrix
```




```
f1_score : 0.9965285696186494
Total Cost due to mis classifiation: 8030
Test Confusion Matrix
```




```
f1_score : 0.7516930022573363
Total Cost due to mis classifiation: 22780
```

Random Forest with mean

In [49]:

```python
parameters = {"max_depth": [3,5,8,10] , "n_estimators":[100,300,500,1000,2000]}


#Gridsearch CV with 2 fold crossvalidation

RF = RandomForestClassifier()
GCV = GridSearchCV(RF,param_grid=parameters, scoring = "f1", verbose = 1,cv=2,n_jobs = -1)
GCV.fit(X_train_mean_std , y_train_mean)
```

```
Fitting 2 folds for each of 20 candidates, totalling 40 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  40 out of  40 | elapsed: 30.5min finished
```

Out[49]:

```
GridSearchCV(cv=2, error_score='raise-deprecating',
             estimator=RandomForestClassifier(bootstrap=True, class_weight=None,
                                              criterion='gini', max_depth=None,
                                              max_features='auto',
                                              max_leaf_nodes=None,
                                              min_impurity_decrease=0.0,
                                              min_impurity_split=None,
                                              min_samples_leaf=1,
                                              min_samples_split=2,
                                              min_weight_fraction_leaf=0.0,
                                              n_estimators='warn', n_jobs=None,
                                              oob_score=False,
                                              random_state=None, verbose=0,
                                              warm_start=False),
             iid='warn', n_jobs=-1,
             param_grid={'max_depth': [3, 5, 8, 10],
                         'n_estimators': [100, 300, 500, 1000, 2000]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring='f1', verbose=1)
```

In [50]:

```python
clf_rf_mean= GCV.best_estimator_
```

In [51]:

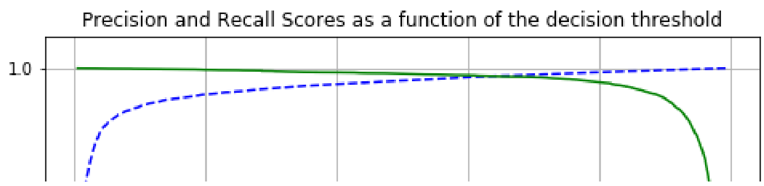
```python
GCV.best_estimator_
```

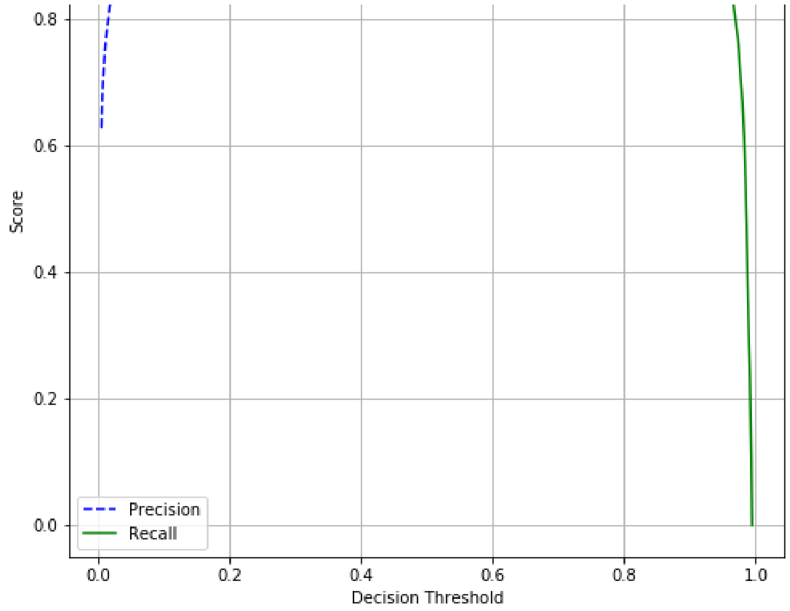
Out[51]:

```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                       max_depth=10, max_features='auto', max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=500,
                       n_jobs=None, oob_score=False, random_state=None,
                       verbose=0, warm_start=False)
```

In [52]:

```python
x_t, x_c, y_t, y_c = train_test_split(X_train_mean_std , y_train_mean, stratify=y_train_mean, test_
size=0.3)
clf_rf_mean.fit(x_t, y_t)
sig_clf_probs = clf_rf_mean.predict_proba(x_c)[:,1]
#train_predict = clf.predict(x_train)
#cross_predict = clf.predict(x_test)
presicision, recall, tresholds =precision_recall_curve(y_c,sig_clf_probs)
plot_precision_recall_vs_threshold(presicision, recall, tresholds)
```





In [53]:

```
t=0.6
```

In [54]:

```
clf= GCV.best_estimator_
clf.fit(X_train_mean_std , y_train_mean)
```

Out[54]:

```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                       max_depth=10, max_features='auto', max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=500,
                       n_jobs=None, oob_score=False, random_state=None,
                       verbose=0, warm_start=False)
```

In [55]:

```
test_clf_probs = clf.predict_proba(X_test_mean_std)[:,1]
train_clf_probs = clf.predict_proba(X_train_mean_std)[:,1]
```

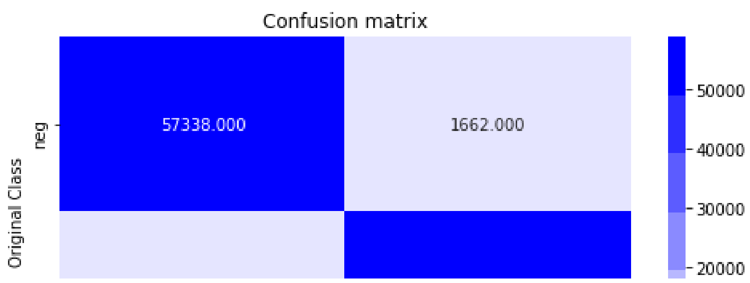
In [56]:

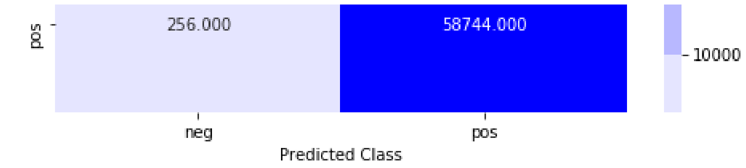
```
train_predictions = pred_with_threshold(train_clf_probs,t)
test_predictions = pred_with_threshold(test_clf_probs,t)
```

In [57]:

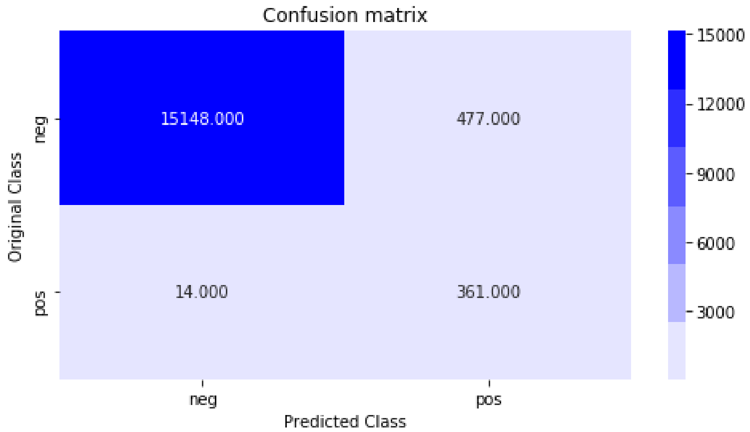
```
print("Train Confusion Matrix")
plot_confusion_matrix(y_train_constant, train_predictions)
print("Test Confusion Matrix")
plot_confusion_matrix(y_test, test_predictions)
```

```
Train Confusion Matrix
```






```
f1_score : 0.9839371555868214
Total Cost due to mis classifiation: 144620
Test Confusion Matrix
```




```
f1_score : 0.5952184666117064
Total Cost due to mis classifiation: 11770
```

Linear\logistic Regression with median

In [52]:

```
parameters = {"alpha": [10 ** x for x in range(-6, 3)], "penalty" : ['l2','l1'], "loss" : ['log','h
inge']}

#Gridsearch CV with 8 fold crossvalidation

LR = SGDClassifier()
GCV = GridSearchCV(LR,param_grid=parameters, scoring = "f1", verbose = 1,cv=8, n_jobs = -1)
GCV.fit(X_train_median_std , y_train_median )
```

```
Fitting 8 folds for each of 36 candidates, totalling 288 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:  2.2min
[Parallel(n_jobs=-1)]: Done 184 tasks      | elapsed:  7.9min
[Parallel(n_jobs=-1)]: Done 288 out of 288 | elapsed:  8.5min finished
```

Out[52]:

```
GridSearchCV(cv=8, error_score='raise-deprecating',
             estimator=SGDClassifier(alpha=0.0001, average=False,
                                     class_weight=None, early_stopping=False,
                                     epsilon=0.1, eta0=0.0, fit_intercept=True,
                                     l1_ratio=0.15, learning_rate='optimal',
                                     loss='hinge', max_iter=1000,
                                     n_iter_no_change=5, n_jobs=None,
                                     penalty='l2', power_t=0.5,
                                     random_state=None, shuffle=True, tol=0.001,
                                     validation_fraction=0.1, verbose=0,
                                     warm_start=False),
             iid='warn', n_jobs=-1,
             param_grid={'alpha': [1e-06, 1e-05, 0.0001, 0.001, 0.01, 0.1, 1,
                                   10, 100],
                         'loss': ['log', 'hinge'], 'penalty': ['l2', 'l1']},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring='f1', verbose=1)
```

In [53]:

```
clf_sgd_median= GCV.best_estimator_
```

In [54]:

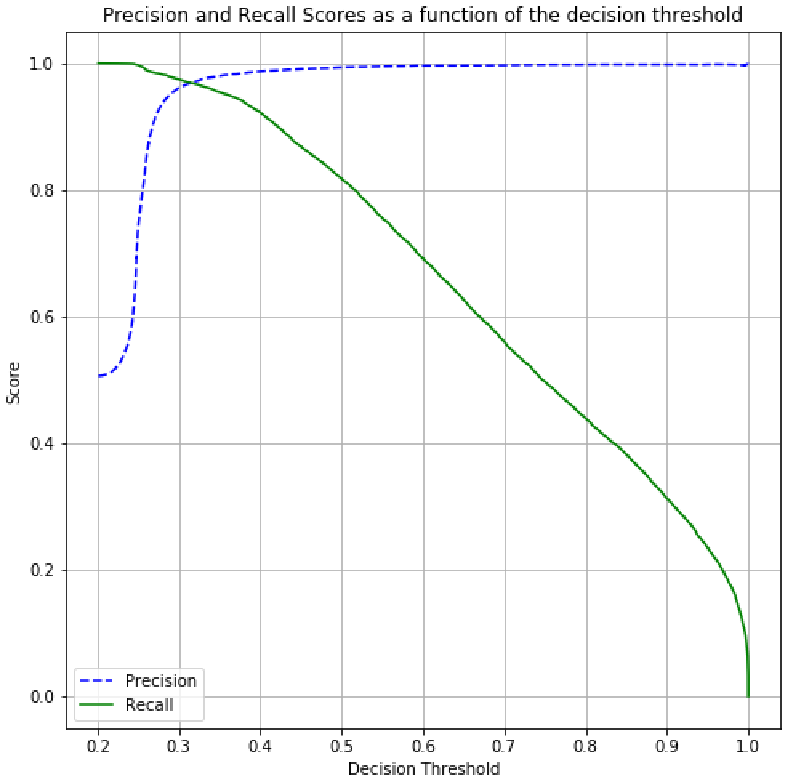
```
GCV.best_estimator_
```

Out[54]:

```
SGDClassifier(alpha=0.0001, average=False, class_weight=None,
              early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True,
              l1_ratio=0.15, learning_rate='optimal', loss='hinge',
              max_iter=1000, n_iter_no_change=5, n_jobs=None, penalty='l2',
              power_t=0.5, random_state=None, shuffle=True, tol=0.001,
              validation_fraction=0.1, verbose=0, warm_start=False)
```

In [55]:

```
x_t, x_c, y_t, y_c = train_test_split(X_train_median_std , y_train_median, stratify=y_train_median,
test_size=0.3)
clf_sgd_median.fit(x_t, y_t)
sig_clf = CalibratedClassifierCV(clf_sgd_median, method="sigmoid")
sig_clf.fit(x_t, y_t)
sig_clf_probs = sig_clf.predict_proba(x_c)[:,1]
presicision, recall, tresholds =precision_recall_curve(y_c,sig_clf_probs)
plot_precision_recall_vs_threshold(presicision, recall, tresholds)
```



In [56]:

```
t=0.32
```

In [57]:

```
clf= GCV.best_estimator_
clf.fit(X_train_median_std , y_train_median)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(X_train_median_std , y_train_median)
test_clf_probs = sig_clf.predict_proba(X_test_median_std)[:,1]
train_clf_probs = sig_clf.predict_proba(X_train_median_std)[:,1]
```

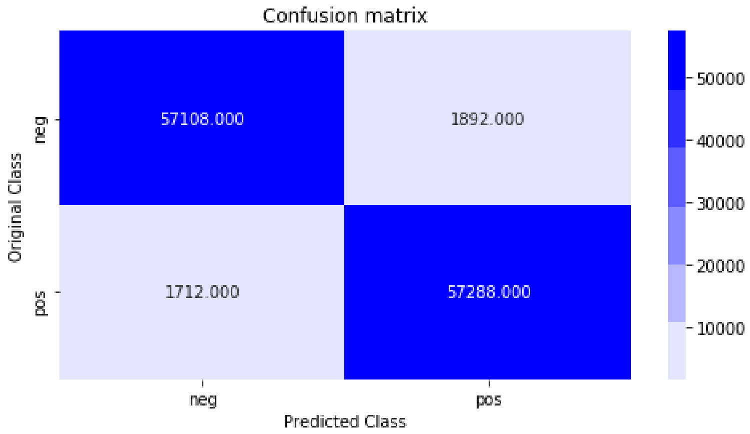
In [58]:

```
train_predictions = pred_with_threshold(train_clf_probs,t)
test_predictions = pred_with_threshold(test_clf_probs,t)
```

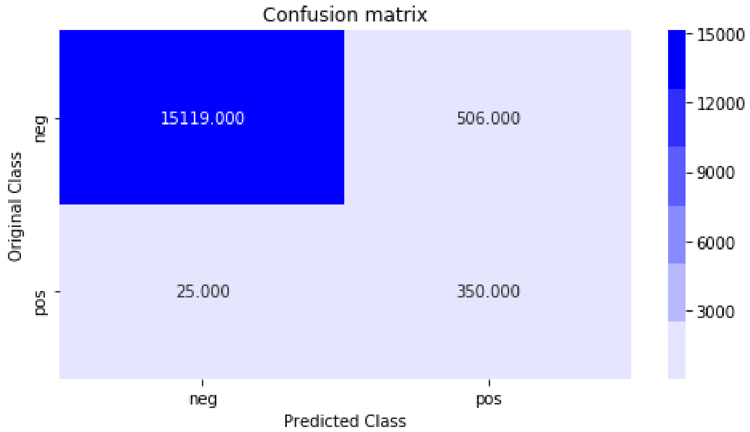
In [59]:

```
print("Train Confusion Matrix")
plot_confusion_matrix(y_train_median, train_predictions)
print("Test Confusion Matrix")
plot_confusion_matrix(y_test, test_predictions)
```

```
Train Confusion Matrix
```




```
f1_score : 0.969504146217634
Total Cost due to mis classifiation: 874920
Test Confusion Matrix
```




```
f1_score : 0.5686433793663689
Total Cost due to mis classifiation: 17560
```

XGB with median

In [38]:

```
parameters = {"max_depth": [5,8,10] , "n_estimators":[300,500,1000,2000]}


#Gridsearch CV with 2 fold crossvalidation

xgb = XGBClassifier()
GCV = GridSearchCV(xgb,param_grid=parameters, scoring = "f1", verbose = 1,cv=2,n_jobs = -1)
GCV.fit(X_train_median_std , y_train_median)
```

```
Fitting 2 folds for each of 12 candidates, totalling 24 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  24 out of  24 | elapsed: 181.5min finished
```

Out[38]:

```
GridSearchCV(cv=2, error_score='raise-deprecating',
             estimator=XGBClassifier(base_score=0.5, booster='gbtree',
                                     colsample_bylevel=1, colsample_bynode=1,
                                     colsample_bytree=1, gamma=0,
                                     learning_rate=0.1, max_delta_step=0,
                                     max_depth=3, min_child_weight=1,
                                     missing=None, n_estimators=100, n_jobs=1,
                                     nthread=None, objective='binary:logistic',
                                     random_state=0, reg_alpha=0, reg_lambda=1,
                                     scale_pos_weight=1, seed=None, silent=None,
                                     subsample=1, verbosity=1),
             iid='warn', n_jobs=-1,
             param_grid={'max_depth': [5, 8, 10],
                         'n_estimators': [300, 500, 1000, 2000]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring='f1', verbose=1)
```

In [39]:

```
clf_xgb_median= GCV.best_estimator_
```

In [40]:

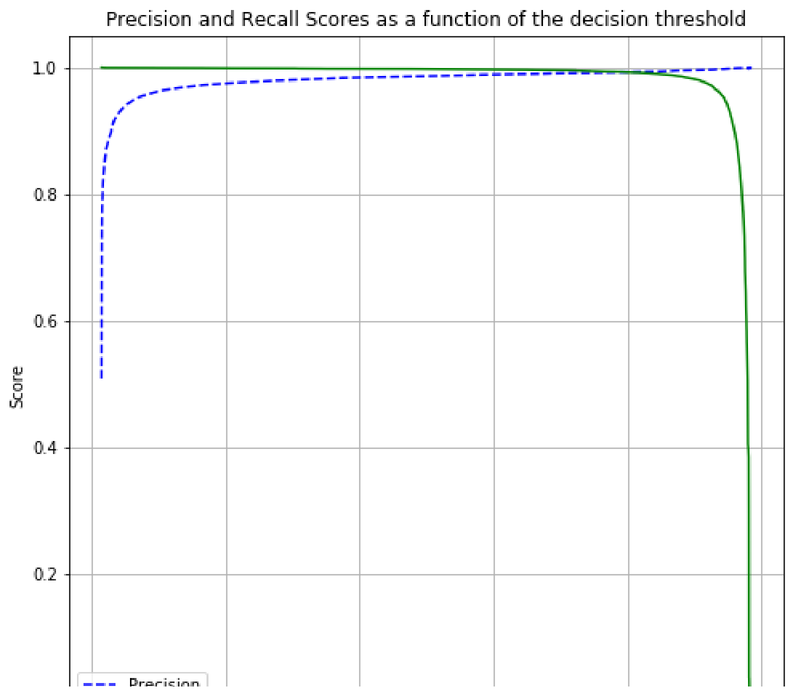
```
GCV.best_estimator_
```

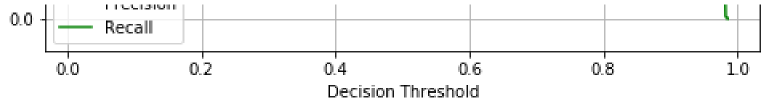
Out[40]:

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0,
              learning_rate=0.1, max_delta_step=0, max_depth=10,
              min_child_weight=1, missing=None, n_estimators=300, n_jobs=1,
              nthread=None, objective='binary:logistic', random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
              silent=None, subsample=1, verbosity=1)
```

In [46]:

```
x_t, x_c, y_t, y_c = train_test_split(X_train_median_std, y_train_median, stratify=y_train_median,
test_size=0.3)
clf_xgb_median.fit(x_t, y_t)
sig_clf_probs = clf_xgb_median.predict_proba(x_c)[:,1]
#train_predict = clf.predict(x_train)
#cross_predict = clf.predict(x_test)
presicision, recall, tresholds =precision_recall_curve(y_c,sig_clf_probs)
plot_precision_recall_vs_threshold(presicision, recall, tresholds)
```





In [47]:

```
t=0.8
```

In [48]:

```
clf_xgb_median.fit(X_train_median_std , y_train_median)
```

Out[48]:

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0,
              learning_rate=0.1, max_delta_step=0, max_depth=10,
              min_child_weight=1, missing=None, n_estimators=300, n_jobs=1,
              nthread=None, objective='binary:logistic', random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
              silent=None, subsample=1, verbosity=1)
```

In [49]:

```
test_clf_probs = clf_xgb_median.predict_proba(X_test_mean_std)[:,1]
train_clf_probs = clf_xgb_median.predict_proba(X_train_mean_std)[:,1]
```

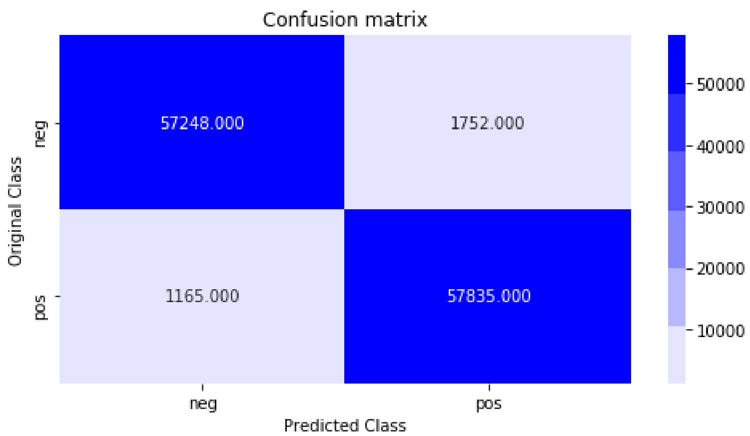
In [50]:

```
train_predictions = pred_with_threshold(train_clf_probs,t)
test_predictions = pred_with_threshold(test_clf_probs,t)
```

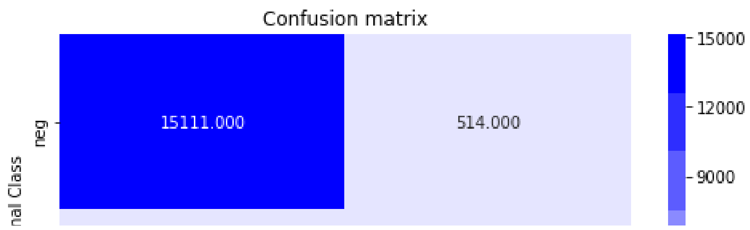
In [51]:

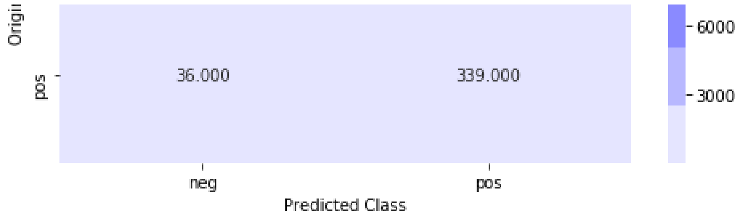
```
print("Train Confusion Matrix")
plot_confusion_matrix(y_train_median, train_predictions)
print("Test Confusion Matrix")
plot_confusion_matrix(y_test, test_predictions)
```

```
Train Confusion Matrix
```




```
f1_score : 0.9754020255171308
Total Cost due to mis classifiation: 600020
Test Confusion Matrix
```






```
f1_score : 0.5521172638436482
Total Cost due to mis classifiation: 23140
```

RandomForest with median

In [48]:

```
parameters = {"max_depth": [3,5,8,10] , "n_estimators":[100,300,500,1000,2000]}


#Gridsearch CV with 2 fold crossvalidation

RF = RandomForestClassifier()
GCV = GridSearchCV(RF,param_grid=parameters, scoring = "f1", verbose = 1,cv=8, n_jobs = -1)
GCV.fit(X_train_median_std, y_train_median)
```

```
Fitting 8 folds for each of 20 candidates, totalling 160 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  42 tasks      | elapsed: 80.0min
[Parallel(n_jobs=-1)]: Done 160 out of 160 | elapsed: 635.4min finished
```

Out[48]:

```
GridSearchCV(cv=8, error_score='raise-deprecating',
       estimator=RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators='warn', n_jobs=None,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False),
       fit_params=None, iid='warn', n_jobs=-1,
       param_grid={'max_depth': [3, 5, 8, 10], 'n_estimators': [100, 300, 500, 1000, 2000]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='f1', verbose=1)
```

In [49]:

```
clf_rf_median= GCV.best_estimator_
```

In [50]:

```
GCV.best_estimator_
```

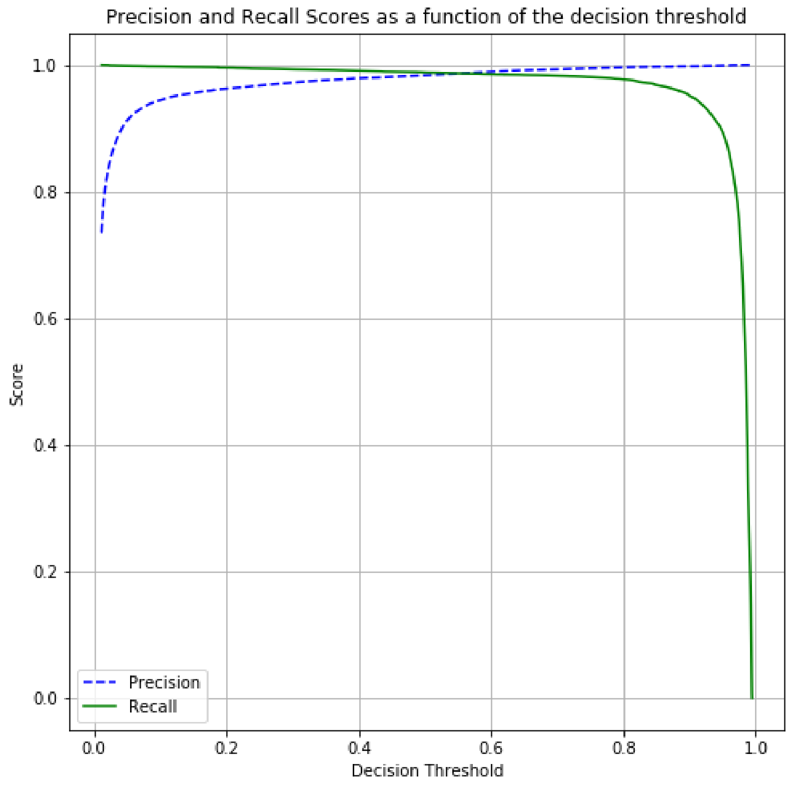
Out[50]:

```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=10, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=300, n_jobs=None,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False)
```

In [54]:

```
x_t, x_c, y_t, y_c = train_test_split(X_train_median_std, y_train_median, stratify=y_train_median,
test_size=0.3)
clf_rf_median.fit(x_t, y_t)
sig_clf_probs = clf_rf_median.predict_proba(x_c)[:,1]
```

```
presicision, recall, tresholds =precision_recall_curve(y_c,sig_clf_probs)
plot_precision_recall_vs_threshold(presicision, recall, tresholds)
```



In [55]:

```
t=0.5
```

In [57]:

```
clf_rf_median.fit(X_train_median_std, y_train_median)
test_clf_probs = clf_rf_median.predict_proba(X_test_median_std)[:,1]
train_clf_probs = clf_rf_median.predict_proba(X_train_median_std)[:,1]
```

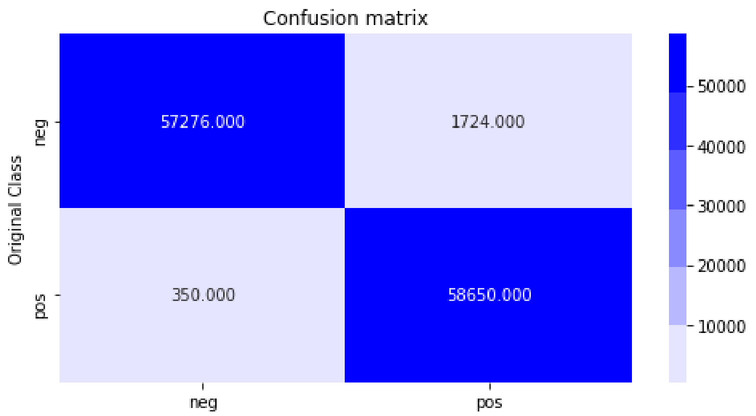
In [58]:

```
train_predictions = pred_with_threshold(train_clf_probs,t)
test_predictions = pred_with_threshold(test_clf_probs,t)
```

In [60]:

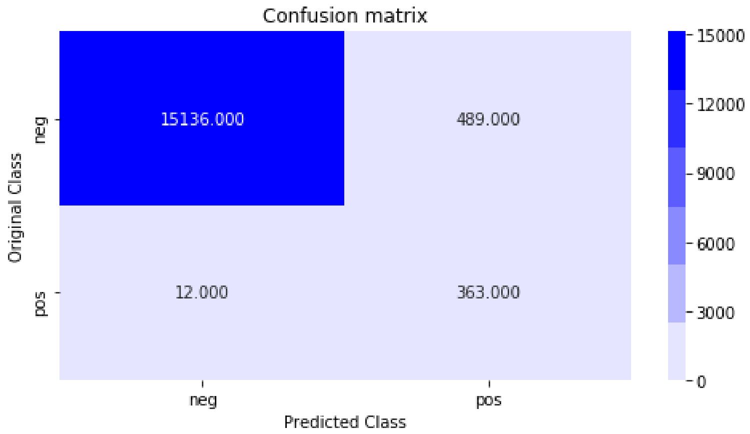
```
print("Train Confusion Matrix")
plot_confusion_matrix(y_train_median, train_predictions)
print("Test Confusion Matrix")
plot_confusion_matrix(y_test, test_predictions)
```

Train Confusion Matrix



Predicted Class

```
f1_score : 0.9826260324693818
Total Cost due to mis classifiation: 192240
Test Confusion Matrix
```




```
f1_score : 0.5916870415647921
Total Cost due to mis classifiation: 10890
```

Linear\logistic Regression with constant value imputation

In [57]:

```
parameters = {"alpha": [10 ** x for x in range(-6, 3)], "penalty" : ['l2','l1'], "loss" : ['log','h
inge']}

#Gridsearch CV with 8 fold crossvalidation

LR = SGDClassifier()
GCV = GridSearchCV(LR,param_grid=parameters, scoring = "f1", verbose = 1,cv=8, n_jobs = -1)
GCV.fit(X_train_constant_std , y_train_constant )
```

```
Fitting 8 folds for each of 36 candidates, totalling 288 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:  1.6min
[Parallel(n_jobs=-1)]: Done 184 tasks      | elapsed:  7.9min
[Parallel(n_jobs=-1)]: Done 288 out of 288 | elapsed:  9.7min finished
```

Out[57]:

```
GridSearchCV(cv=8, error_score='raise-deprecating',
             estimator=SGDClassifier(alpha=0.0001, average=False,
                                     class_weight=None, early_stopping=False,
                                     epsilon=0.1, eta0=0.0, fit_intercept=True,
                                     l1_ratio=0.15, learning_rate='optimal',
                                     loss='hinge', max_iter=1000,
                                     n_iter_no_change=5, n_jobs=None,
                                     penalty='l2', power_t=0.5,
                                     random_state=None, shuffle=True, tol=0.001,
                                     validation_fraction=0.1, verbose=0,
                                     warm_start=False),
             iid='warn', n_jobs=-1,
             param_grid={'alpha': [1e-06, 1e-05, 0.0001, 0.001, 0.01, 0.1, 1,
                                   10, 100],
                         'loss': ['log', 'hinge'], 'penalty': ['l2', 'l1']},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring='f1', verbose=1)
```

In [58]:

```
clf_sgd_constant= GCV.best_estimator_
```

In [59]:

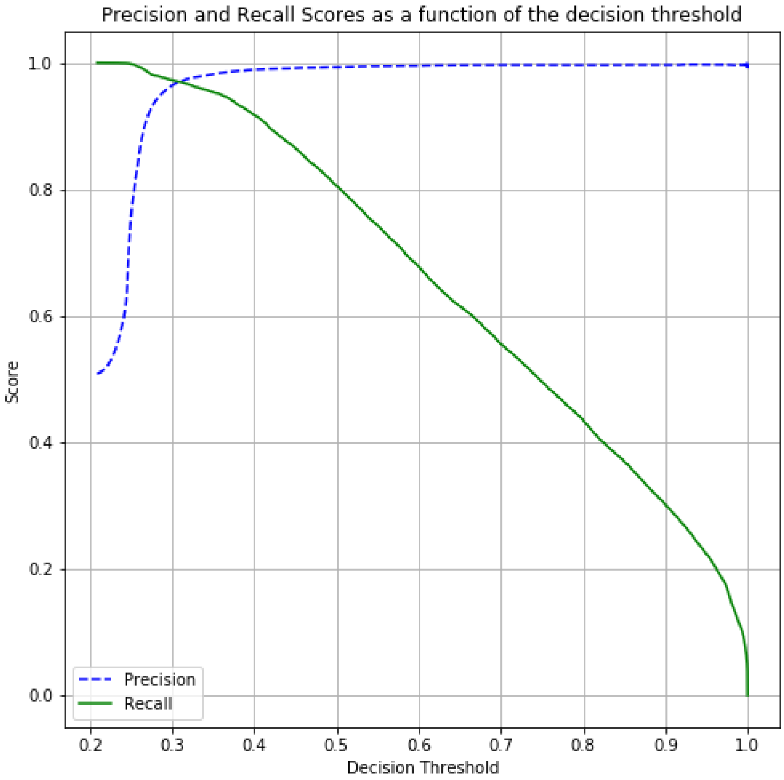
```
GCV.best_estimator_
```

Out[59]:

```
SGDClassifier(alpha=0.0001, average=False, class_weight=None,
              early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True,
              l1_ratio=0.15, learning_rate='optimal', loss='hinge',
              max_iter=1000, n_iter_no_change=5, n_jobs=None, penalty='l2',
              power_t=0.5, random_state=None, shuffle=True, tol=0.001,
              validation_fraction=0.1, verbose=0, warm_start=False)
```

In [60]:

```
x_t, x_c, y_t, y_c = train_test_split(X_train_constant_std , y_train_constant, stratify=y_train_con
stant, test_size=0.3)
clf_sgd_constant.fit(x_t, y_t)
sig_clf = CalibratedClassifierCV(clf_sgd_constant, method="sigmoid")
sig_clf.fit(x_t, y_t)
sig_clf_probs = sig_clf.predict_proba(x_c)[:,1]
presicision, recall, tresholds =precision_recall_curve(y_c,sig_clf_probs)
plot_precision_recall_vs_threshold(presicision, recall, tresholds)
```



In [61]:

```
t=0.3
```

In [62]:

```
clf= GCV.best_estimator_
clf.fit(X_train_constant_std , y_train_constant)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(X_train_constant_std , y_train_constant)
test_clf_probs = sig_clf.predict_proba(X_test_constant_std)[:,1]
train_clf_probs = sig_clf.predict_proba(X_train_constant_std)[:,1]
```

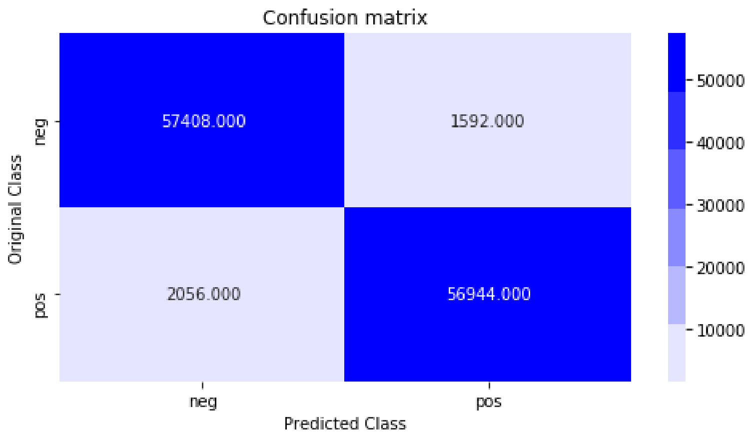
In [63]:

```
train_predictions = pred_with_threshold(train_clf_probs,t)
test_predictions = pred_with_threshold(test_clf_probs,t)
```

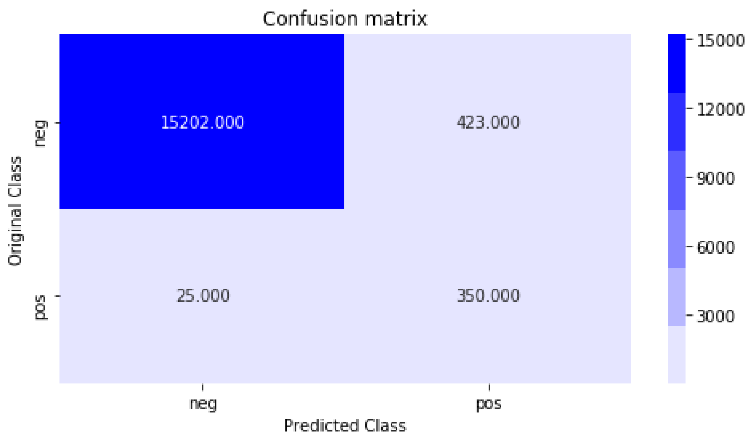
In [64]:

```
print("Train Confusion Matrix")
plot_confusion_matrix(y_train_constant, train_predictions)
print("Test Confusion Matrix")
plot_confusion_matrix(y_test, test_predictions)
```

```
Train Confusion Matrix
```




```
f1_score : 0.9689627007895454
Total Cost due to mis classifiation: 1043920
Test Confusion Matrix
```




```
f1_score : 0.6097560975609756
Total Cost due to mis classifiation: 16730
```

XGB with constant value imputation

In [42]:

```
parameters = {"max_depth": [5,8,10] , "n_estimators":[300,500,1000,2000]}


#Gridsearch CV with 2 fold crossvalidation

xgb = XGBClassifier()
GCV = GridSearchCV(xgb,param_grid=parameters, scoring = "f1", verbose = 1,cv=2,n_jobs = -1)
GCV.fit(X_train_constant_std , y_train_constant)
```

```
Fitting 2 folds for each of 12 candidates, totalling 24 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  24 out of  24 | elapsed: 131.2min finished
```

Out[42]:

```
GridSearchCV(cv=2, error_score='raise-deprecating',
             estimator=XGBClassifier(base_score=0.5, booster='gbtree',
                                     colsample_bylevel=1, colsample_bynode=1,
```

```
                                             colsample_bytree=1, gamma=0,
                                             learning_rate=0.1, max_delta_step=0,
                                             max_depth=3, min_child_weight=1,
                                             missing=None, n_estimators=100, n_jobs=1,
                                             nthread=None, objective='binary:logistic',
                                             random_state=0, reg_alpha=0, reg_lambda=1,
                                             scale_pos_weight=1, seed=None, silent=None,
                                             subsample=1, verbosity=1),
             iid='warn', n_jobs=-1,
             param_grid={'max_depth': [5, 8, 10],
                         'n_estimators': [300, 500, 1000, 2000]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring='f1', verbose=1)
```

In [43]:

```
clf_xgb_constant= GCV.best_estimator_
```

In [44]:

```
GCV.best_estimator_
```

Out[44]:

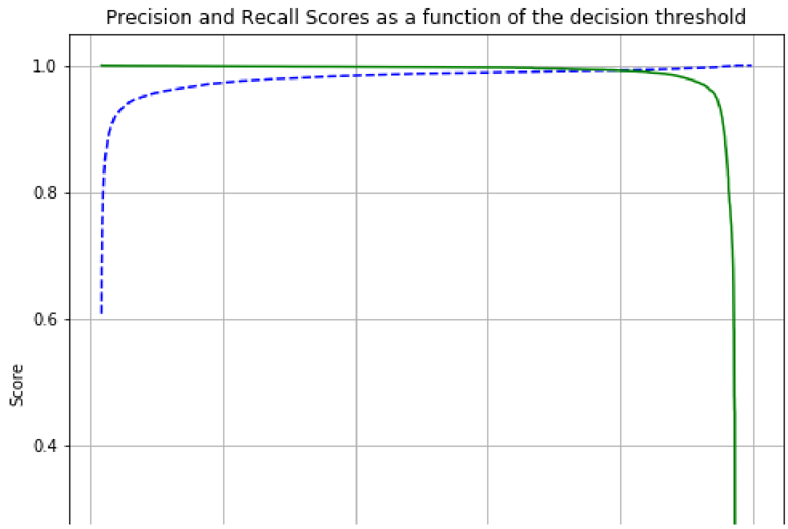
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0,
              learning_rate=0.1, max_delta_step=0, max_depth=10,
              min_child_weight=1, missing=None, n_estimators=300, n_jobs=1,
              nthread=None, objective='binary:logistic', random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
              silent=None, subsample=1, verbosity=1)
```

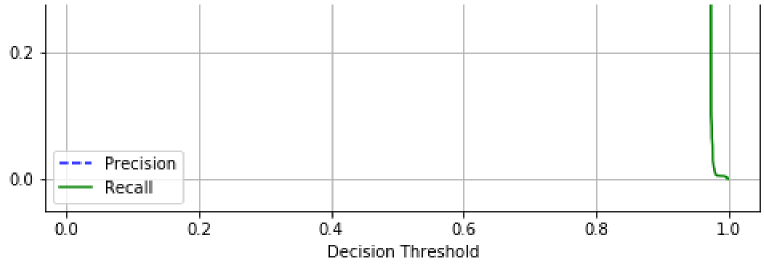
In [85]:

```
clf_xgb_constant = XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0,
              learning_rate=0.1, max_delta_step=0, max_depth=10,
              min_child_weight=1, missing=None, n_estimators=300, n_jobs=1,
              nthread=None, objective='binary:logistic', random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
              silent=None, subsample=1, verbosity=1)
```

In [86]:

```
x_t, x_c, y_t, y_c = train_test_split(X_train_constant_std, y_train_constant, stratify=y_train_cons
tant, test_size=0.3)
clf_xgb_constant.fit(x_t, y_t)
sig_clf_probs = clf_xgb_constant.predict_proba(x_c)[:,1]
#train_predict = clf.predict(x_train)
#cross_predict = clf.predict(x_test)
presicision, recall, tresholds =precision_recall_curve(y_c,sig_clf_probs)
plot_precision_recall_vs_threshold(presicision, recall, tresholds)
```





In [87]:

```
t=0.8
```

In [88]:

```
clf_xgb_constant.fit(X_train_constant_std , y_train_constant)
```

Out[88]:

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0,
              learning_rate=0.1, max_delta_step=0, max_depth=10,
              min_child_weight=1, missing=None, n_estimators=300, n_jobs=1,
              nthread=None, objective='binary:logistic', random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
              silent=None, subsample=1, verbosity=1)
```

In [89]:

```
test_clf_probs = clf_xgb_constant.predict_proba(X_test_constant_std)[:,1]
train_clf_probs = clf_xgb_constant.predict_proba(X_train_constant_std)[:,1]
```

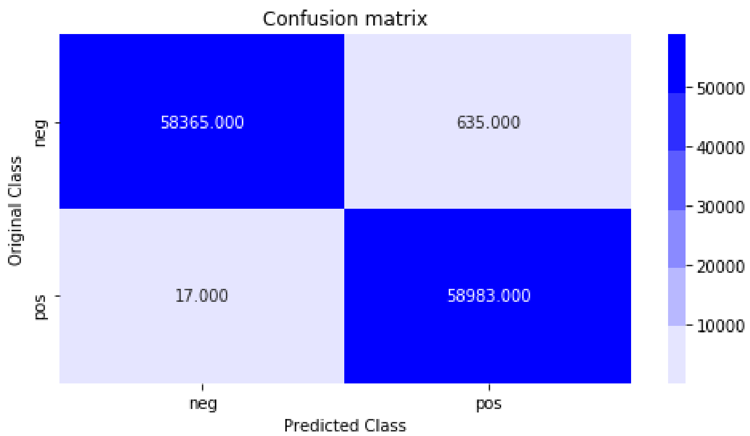
In [90]:

```
train_predictions = pred_with_threshold(train_clf_probs,t)
test_predictions = pred_with_threshold(test_clf_probs,t)
```

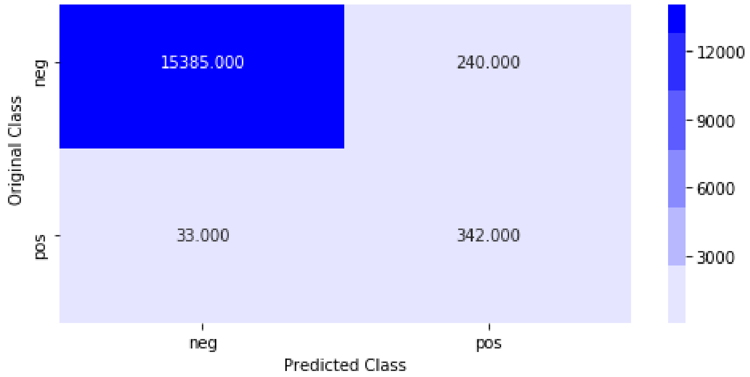
In [91]:

```
print("Train Confusion Matrix")
plot_confusion_matrix(y_train_constant, train_predictions)
print("Test Confusion Matrix")
plot_confusion_matrix(y_test, test_predictions)
```

Train Confusion Matrix




```
f1_score : 0.9945033637390615
Total Cost due to mis classifiation: 14850
Test Confusion Matrix
```




```
f1_score : 0.7147335423197493
Total Cost due to mis classifiation: 18900
```

Random Forest with constant value imputation

In [92]:

```
parameters = {"max_depth": [3,5,8,10] , "n_estimators":[100,300,500,1000,2000]}


#Gridsearch CV with 2 fold crossvalidation

RF = RandomForestClassifier()
GCV = GridSearchCV(RF,param_grid=parameters, scoring = "f1", verbose = 1,cv=2,n_jobs =-1)
GCV.fit(X_train_constant_std , y_train_constant)
```

```
Fitting 2 folds for each of 20 candidates, totalling 40 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  40 out of  40 | elapsed: 30.4min finished
```

Out[92]:

```
GridSearchCV(cv=2, error_score='raise-deprecating',
             estimator=RandomForestClassifier(bootstrap=True, class_weight=None,
                                              criterion='gini', max_depth=None,
                                              max_features='auto',
                                              max_leaf_nodes=None,
                                              min_impurity_decrease=0.0,
                                              min_impurity_split=None,
                                              min_samples_leaf=1,
                                              min_samples_split=2,
                                              min_weight_fraction_leaf=0.0,
                                              n_estimators='warn', n_jobs=None,
                                              oob_score=False,
                                              random_state=None, verbose=0,
                                              warm_start=False),
             iid='warn', n_jobs=-1,
             param_grid={'max_depth': [3, 5, 8, 10],
                         'n_estimators': [100, 300, 500, 1000, 2000]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring='f1', verbose=1)
```

In [93]:

```
clf_rf_constant= GCV.best_estimator_
```

In [94]:

```
GCV.best_estimator_
```

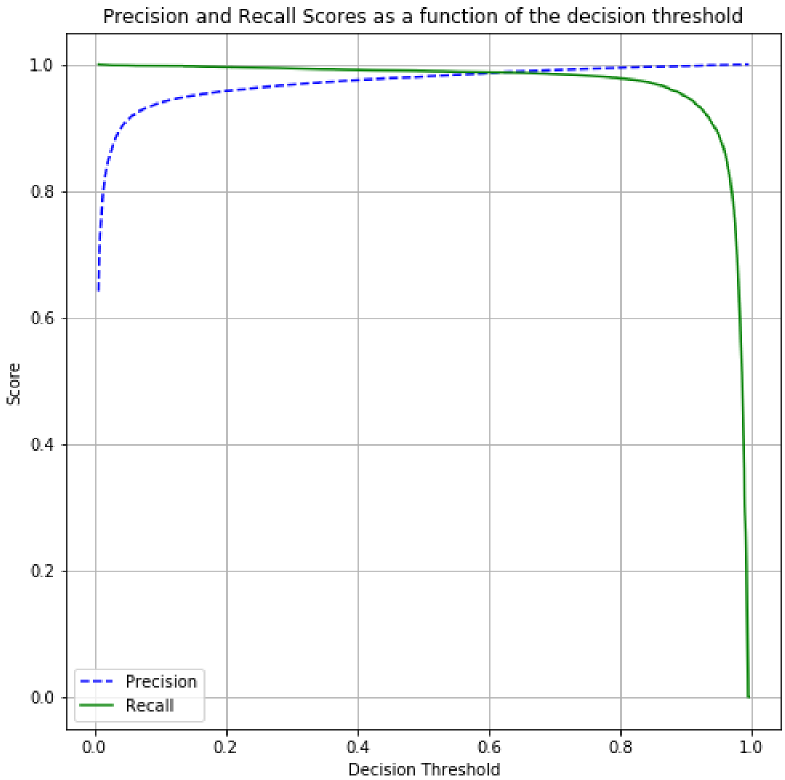
Out[94]:

```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                       max_depth=10, max_features='auto', max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
```

```
                         min_weight_fraction_leaf=0.0, n_estimators=300,
                         n_jobs=None, oob_score=False, random_state=None,
                         verbose=0, warm_start=False)
```

In [95]:

```
x_t, x_c, y_t, y_c = train_test_split(X_train_constant_std , y_train_constant, stratify=y_train_con
stant, test_size=0.3)
clf_rf_constant.fit(x_t, y_t)
sig_clf_probs = clf_rf_constant.predict_proba(x_c)[:,1]
#train_predict = clf.predict(x_train)
#cross_predict = clf.predict(x_test)
presicision, recall, tresholds =precision_recall_curve(y_c,sig_clf_probs)
plot_precision_recall_vs_threshold(presicision, recall, tresholds)
```



In [96]:

```
t=0.6
```

In [97]:

```
clf_rf_constant.fit(X_train_constant_std , y_train_constant)
```

Out[97]:

```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                       max_depth=10, max_features='auto', max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=300,
                       n_jobs=None, oob_score=False, random_state=None,
                       verbose=0, warm_start=False)
```

In [98]:

```
test_clf_probs = clf_rf_constant.predict_proba(X_test_constant_std)[:,1]
train_clf_probs = clf_rf_constant.predict_proba(X_train_constant_std)[:,1]
```

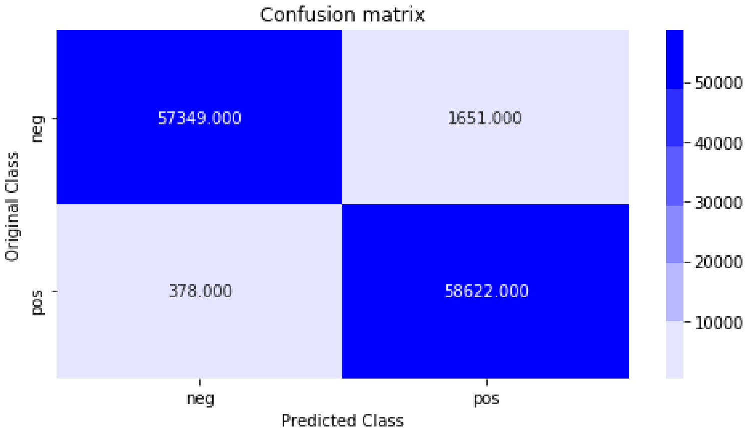
In [99]:

```
train_predictions = pred_with_threshold(train_clf_probs,t)
test_predictions = pred_with_threshold(test_clf_probs,t)
```

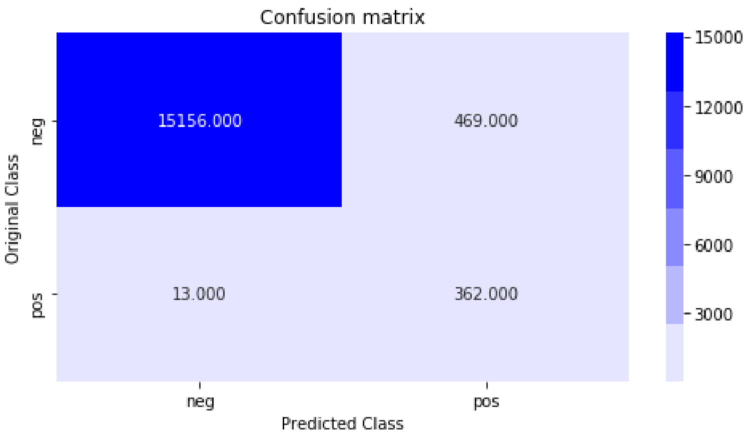
In [100]:

```
print("Train Confusion Matrix")
plot_confusion_matrix(y_train_constant, train_predictions)
print("Test Confusion Matrix")
plot_confusion_matrix(y_test, test_predictions)
```

```
Train Confusion Matrix
```




```
f1_score : 0.9829886059711753
Total Cost due to mis classifiation: 205510
Test Confusion Matrix
```




```
f1_score : 0.6003316749585407
Total Cost due to mis classifiation: 11190
```

Trying with dimensionality reduction techniques

- Random Forest classifier with medain value imputation given good results till now, so we will proceed with dimensionality reduction.

PCA

In [68]:

```
pca = PCA()
train_pca = pca.fit(x_train_median)
```

In [69]:

```
explained_variance = pca.explained_variance_ratio_
```

In [70]:

```
explained_variance_sorted = np.sort(explained_variance)
```

In [71]:

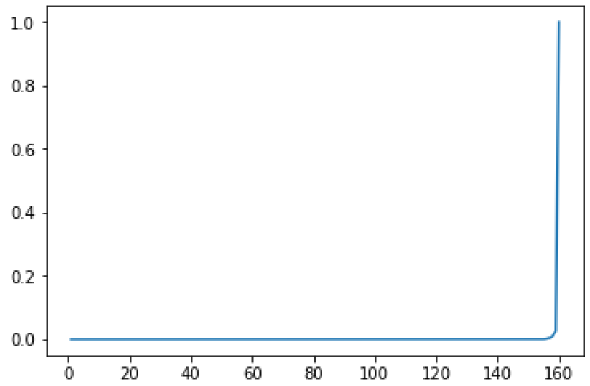
```
length = len(explained_variance_sorted)
```

In [72]:

```
cumsum = pd.Series(explained_variance_sorted).cumsum()
```

In [73]:

```
plt.plot(range(1,length+1),cumsum)
plt.show()
```



In [74]:

```
pca = PCA(n_components=20)
train_pca = pca.fit(x_train_median)
```

In [75]:

```
pca.explained_variance_ratio_.sum()
```

Out[75]:

```
0.9999686390849858
```

In [76]:

```
x_train_median_pca = pca.transform(x_train_median)
x_test_median_pca = pca.transform(x_test_median)
```

In [77]:

```
sm = SMOTE(random_state=2)
X_train_median_sm_pca, y_train_median_pca = sm.fit_sample(x_train_median_pca, y_train.ravel())
```

In [78]:

```
ss = StandardScaler()
X_train_pca_std = ss.fit_transform(X_train_median_sm_pca)
X_test_pca_std = ss.transform(x_test_median_pca)
```

In [79]:

```
parameters = {"max_depth": [3,5,8,10] , "n_estimators":[100,300,500,1000,2000]}


#Gridsearch CV with 2 fold crossvalidation
```

```
RF = RandomForestClassifier()
GCV = GridSearchCV(RF,param_grid=parameters, scoring = "f1", verbose = 1,cv=2, n_jobs = -1)
GCV.fit(X_train_pca_std, y_train_median_pca)
```

```
Fitting 2 folds for each of 20 candidates, totalling 40 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  40 out of  40 | elapsed: 15.4min finished
```

Out[79]:

```
GridSearchCV(cv=2, error_score='raise-deprecating',
             estimator=RandomForestClassifier(bootstrap=True, class_weight=None,
                                              criterion='gini', max_depth=None,
                                              max_features='auto',
                                              max_leaf_nodes=None,
                                              min_impurity_decrease=0.0,
                                              min_impurity_split=None,
                                              min_samples_leaf=1,
                                              min_samples_split=2,
                                              min_weight_fraction_leaf=0.0,
                                              n_estimators='warn', n_jobs=None,
                                              oob_score=False,
                                              random_state=None, verbose=0,
                                              warm_start=False),
             iid='warn', n_jobs=-1,
             param_grid={'max_depth': [3, 5, 8, 10],
                         'n_estimators': [100, 300, 500, 1000, 2000]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring='f1', verbose=1)
```

In [80]:

```
clf_rf_pca= GCV.best_estimator_
```

In [81]:

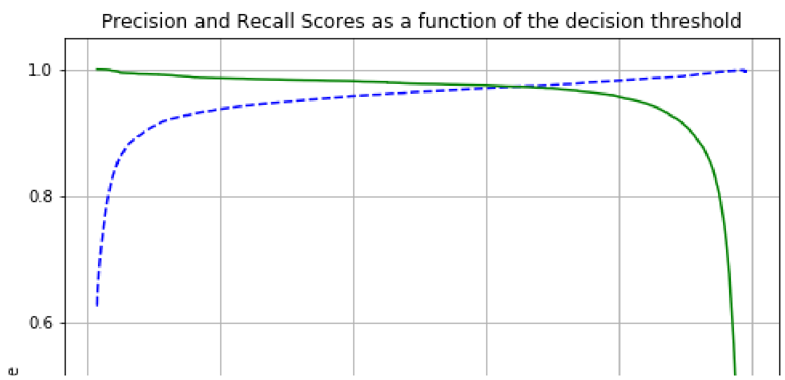
```
GCV.best_estimator_
```

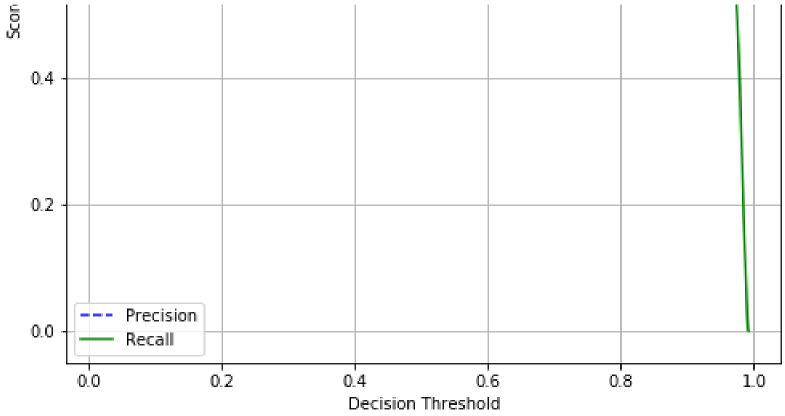
Out[81]:

```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                       max_depth=10, max_features='auto', max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=2000,
                       n_jobs=None, oob_score=False, random_state=None,
                       verbose=0, warm_start=False)
```

In [82]:

```
x_t, x_c, y_t, y_c = train_test_split(X_train_pca_std , y_train_median_pca,
stratify=y_train_median_pca, test_size=0.3)
clf_rf_pca.fit(x_t, y_t)
sig_clf_probs = clf_rf_pca.predict_proba(x_c)[:,1]
presicision, recall, tresholds =precision_recall_curve(y_c,sig_clf_probs)
plot_precision_recall_vs_threshold(presicision, recall, tresholds)
```





In [83]:

```
t=0.6
```

In [84]:

```
clf_rf_pca.fit(X_train_pca_std , y_train_median_pca)
```

Out[84]:

```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                       max_depth=10, max_features='auto', max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=2000,
                       n_jobs=None, oob_score=False, random_state=None,
                       verbose=0, warm_start=False)
```

In [85]:

```
test_clf_probs = clf_rf_pca.predict_proba(X_test_pca_std)[:,1]
train_clf_probs = clf_rf_pca.predict_proba(X_train_pca_std)[:,1]
```

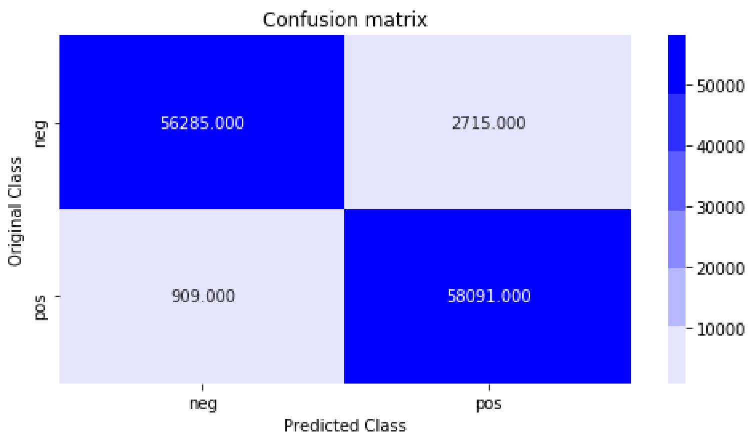
In [86]:

```
train_predictions = pred_with_threshold(train_clf_probs,t)
test_predictions = pred_with_threshold(test_clf_probs,t)
```

In [87]:

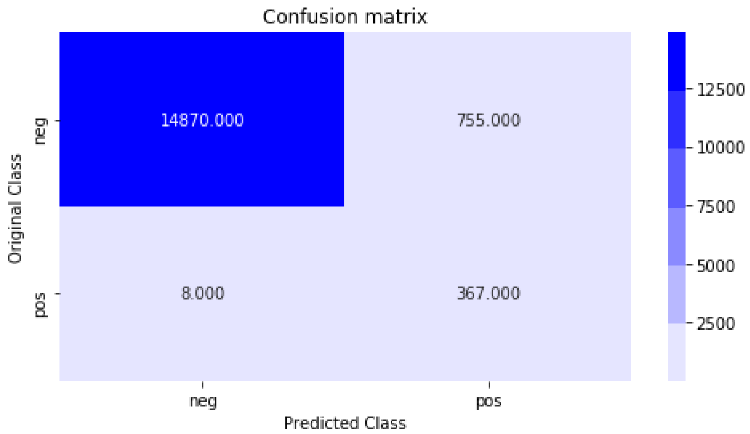
```
print("Train Confusion Matrix")
plot_confusion_matrix(y_train_median_pca, train_predictions)
print("Test Confusion Matrix")
plot_confusion_matrix(y_test, test_predictions)
```

```
Train Confusion Matrix
```




```
f1_score : 0.9697510976077992
Total Cost due to mis-classification: 481650
```

Total Cost due to mis classifiation: 481650
Test Confusion Matrix



f1_score : 0.4903139612558451
Total Cost due to mis classifiation: 11550

SVD

In [69]:

```
from sklearn.decomposition import PCA, TruncatedSVD
```

In [94]:

```
# Taking 30 features
svd = TruncatedSVD(n_components=30)
train_svd = svd.fit(x_train_median)
```

In [95]:

```
svd.explained_variance_ratio_.sum()
```

Out[95]:

0.9999854134465792

In [96]:

```
x_train_median_svd = svd.transform(x_train_median)
x_test_median_svd = svd.transform(x_test_median)
```

In [97]:

```
sm = SMOTE(random_state=2)
X_train_median_sm_svd, y_train_median_svd = sm.fit_sample(x_train_median_svd, y_train.ravel())
```

In [98]:

```
ss = StandardScaler()
X_train_svd_std = ss.fit_transform(X_train_median_sm_svd)
X_test_svd_std = ss.transform(x_test_median_svd)
```

In [99]:

```
parameters = {"max_depth": [3,5,8,10] , "n_estimators":[100,300,500,1000,2000]}


#Gridsearch CV with 2 fold crossvalidation

RF = RandomForestClassifier()
GCV = GridSearchCV(RF,param_grid=parameters, scoring = "f1", verbose = 1,cv=2, n_jobs = -1)
```

```
GCV.fit(X_train_svd_std, y_train_median_svd)
```

```
Fitting 2 folds for each of 20 candidates, totalling 40 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  40 out of  40 | elapsed: 34.9min finished
```

Out[99]:

```
GridSearchCV(cv=2, error_score='raise-deprecating',
             estimator=RandomForestClassifier(bootstrap=True, class_weight=None,
                                              criterion='gini', max_depth=None,
                                              max_features='auto',
                                              max_leaf_nodes=None,
                                              min_impurity_decrease=0.0,
                                              min_impurity_split=None,
                                              min_samples_leaf=1,
                                              min_samples_split=2,
                                              min_weight_fraction_leaf=0.0,
                                              n_estimators='warn', n_jobs=None,
                                              oob_score=False,
                                              random_state=None, verbose=0,
                                              warm_start=False),
             iid='warn', n_jobs=-1,
             param_grid={'max_depth': [3, 5, 8, 10],
                         'n_estimators': [100, 300, 500, 1000, 2000]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring='f1', verbose=1)
```

In [100]:

```
clf_rf_svd= GCV.best_estimator_
```

In [101]:

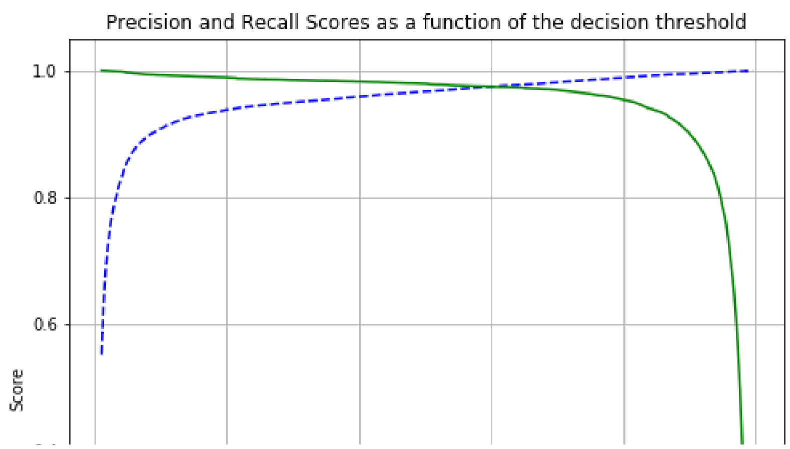
```
GCV.best_estimator_
```

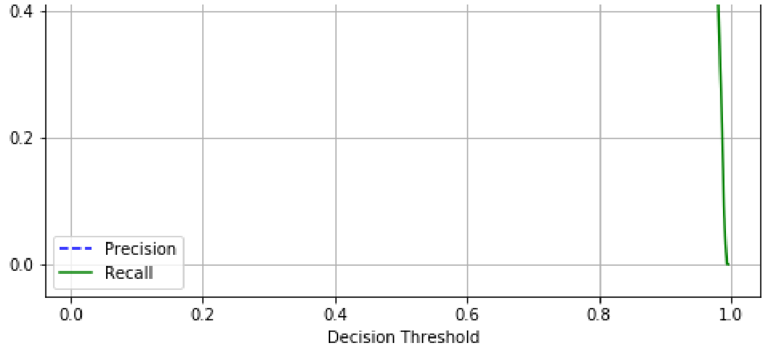
Out[101]:

```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                       max_depth=10, max_features='auto', max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=100,
                       n_jobs=None, oob_score=False, random_state=None,
                       verbose=0, warm_start=False)
```

In [102]:

```
x_t, x_c, y_t, y_c = train_test_split(X_train_svd_std , y_train_median_svd,
stratify=y_train_median_svd, test_size=0.3)
clf_rf_svd.fit(x_t, y_t)
sig_clf_probs = clf_rf_svd.predict_proba(x_c)[:,1]
presicision, recall, tresholds =precision_recall_curve(y_c,sig_clf_probs)
plot_precision_recall_vs_threshold(presicision, recall, tresholds)
```





In [104]:

```
clf_rf_svd.fit(X_train_svd_std , y_train_median_svd)
```

Out[104]:

```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                       max_depth=10, max_features='auto', max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=100,
                       n_jobs=None, oob_score=False, random_state=None,
                       verbose=0, warm_start=False)
```

In [106]:

```
test_clf_probs = clf_rf_svd.predict_proba(X_test_svd_std)[:,1]
train_clf_probs = clf_rf_svd.predict_proba(X_train_svd_std)[:,1]
```

In [134]:

```
# taking 0.4, since recall is high eith very little decrease in the precision
t=0.4
```

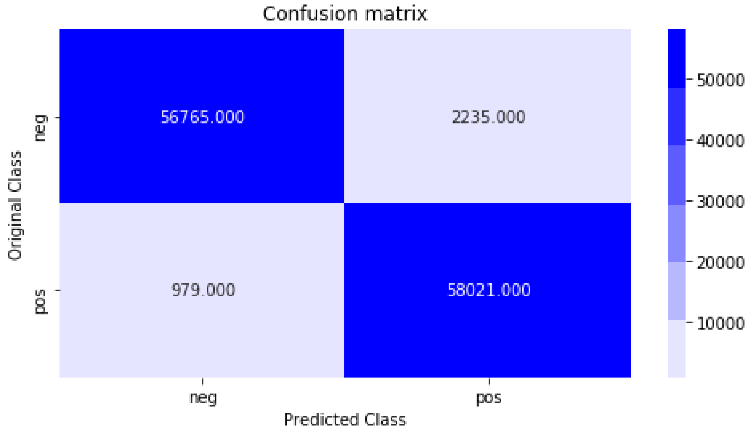
In [135]:

```
train_predictions = pred_with_threshold(train_clf_probs,t)
test_predictions = pred_with_threshold(test_clf_probs,t)
```

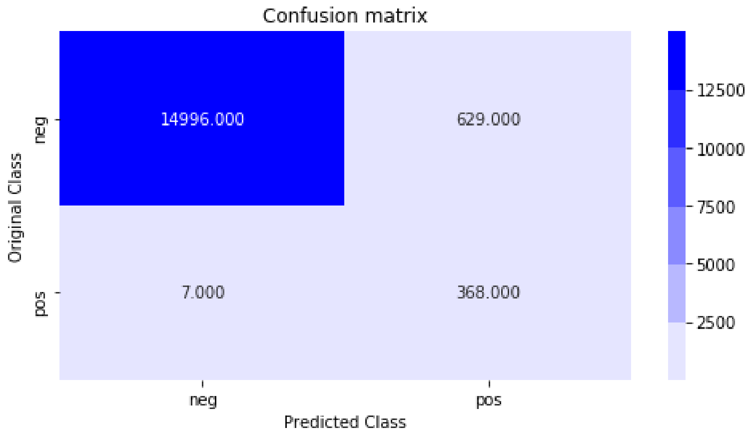
In [136]:

```
print("Train Confusion Matrix")
plot_confusion_matrix(y_train_median_svd, train_predictions)
print("Test Confusion Matrix")
plot_confusion_matrix(y_test, test_predictions)
```

```
Train Confusion Matrix
```




```
f1_score : 0.9730495740256255
Total Cost due to mis classifiation: 511850
Test Confusion Matrix
```




```
f1_score : 0.5364431486880467
Total Cost due to mis classifiation: 9790
```

Conclusions

In [132]:

```python
from prettytable import PrettyTable
```

In [133]:

```python
pt=PrettyTable()
pt.field_names=["model","imputation_method","f1-score","total_cost"]
pt.add_row(["sgd-hinge","Mean","0.59","13800"])
pt.add_row(["random_forest","Mean","0.60","11770"])
pt.add_row(["XGBoost","Mean","0.75","22780"])
pt.add_row(["sgd-hinge","Median","0.57","17560"])
pt.add_row(["random_forest","Median","0.59","10890"])
pt.add_row(["XGBoost","Median","0.55","23140"])
pt.add_row(["sgd-hinge","constant_value","0.60","16730"])
pt.add_row(["random_forest","constant_value","0.60","11190"])
pt.add_row(["XGBoost","constant_value","0.71","18900"])
pt.add_row(["PCA-0.6","constant_value","0.49","11550"])
pt.add_row(["svd-0.4","Median","0.53","9790"])
print(pt)
```

```
+---------------+-------------------+----------+------------+
|     model     | imputation_method | f1-score | total_cost |
+---------------+-------------------+----------+------------+
|   sgd-hinge   |        Mean       |   0.59   |   13800    |
| random_forest |        Mean       |   0.60   |   11770    |
|    XGBoost    |        Mean       |   0.75   |   22780    |
|   sgd-hinge   |       Median      |   0.57   |   17560    |
| random_forest |       Median      |   0.59   |   10890    |
|    XGBoost    |       Median      |   0.55   |   23140    |
|   sgd-hinge   |   constant_value  |   0.60   |   16730    |
| random_forest |   constant_value  |   0.60   |   11190    |
|    XGBoost    |   constant_value  |   0.71   |   18900    |
|    PCA-0.6    |   constant_value  |   0.49   |   11550    |
|    svd-0.4    |       Median      |   0.53   |    9790    |
+---------------+-------------------+----------+------------+
```

From the above results we coud conclude that,

- Random forest classidier with median value imputation after applyind dimensionality reduction technique given good results.
- Many features are not important for the prediction, since out of 160 features, if we take 30 features we could able preserve 99.99% of varaince.
- So I have reduced the dimensions using SVD.
- with our best model we got the minimum cost of 9790.