In [1]:
```python
#import libraries....

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
import folium

from sklearn.model_selection import train_test_split
from sklearn.metrics import log_loss,confusion_matrix,f1_score
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import SGDClassifier,LogisticRegression
from sklearn.model_selection import RandomizedSearchCV
from sklearn.tree import DecisionTreeClassifier
from sklearn.calibration import CalibratedClassifierCV
from sklearn.naive_bayes import MultinomialNB,GaussianNB
import lightgbm as lgb
from sklearn.model_selection import StratifiedKFold
import xgboost as xgb
from mlxtend.classifier import StackingClassifier
from sklearn.preprocessing import Normalizer,MinMaxScaler,StandardScaler

import xgboost as xgb
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import RandomizedSearchCV
from sklearn.preprocessing import LabelEncoder



import datetime

import warnings
warnings.filterwarnings("ignore")
```

Choosing metric

- From EDA part, It is sure that there is high class imbalance in the dataset. Also review_score 1,2,3 are very important, since misclassification of them would cause customer loss to the seller. So False positive should be the concern here.
- Here precision and recall of each class is important. Precision of class 4,5 is more important and recall of 1,2,3 class is very important. So we can use f1 score,which is a combination of precision and recall, Since each is important to us we can consider Macro f1 score..
- Based on this observation and business problem, I choose Macro F1 score as metric. Also I want to check multi-class confusion matrix, so that we can observe the misclassification easily.

Metric choosen,

```
* Macro F1 score
* Multi-class Confusion matrix
```

In [2]:
```python
#load the data with all created features
data = pd.read_csv("data_with_advanced_features.csv")
data.drop("Unnamed: 0", inplace=True, axis=1)
```

In [3]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 113105 entries, 0 to 113104
Data columns (total 71 columns):
 #   Column                         Non-Null Count   Dtype
---  ------                         --------------   -----
 0   order_id                       113105 non-null  object
 1   payment_sequential             113105 non-null  int64
 2   payment_type                   113105 non-null  object
 3   payment_installments           113105 non-null  int64
 4   payment_value                  113105 non-null  float64
 5   customer_id                    113105 non-null  object
 6   order_status                   113105 non-null  object
 7   order_purchase_timestamp       113105 non-null  object
 8   order_approved_at              113105 non-null  object
 9   order_delivered_carrier_date   113105 non-null  object
 10  order_delivered_customer_date  113105 non-null  object
 11  order_estimated_delivery_date  113105 non-null  object
 12  review_score                   113105 non-null  int64
 13  customer_unique_id             113105 non-null  object
 14  zip_code_prefix_customer       113105 non-null  int64
 15  lat_customer                   113105 non-null  float64
 16  lng_customer                   113105 non-null  float64
 17  customer_city                  113105 non-null  object
 18  customer_state                 113105 non-null  object
 19  product_id                     113105 non-null  object
 20  product_name_lenght            113105 non-null  float64
 21  product_description_lenght     113105 non-null  float64
 22  product_photos_qty             113105 non-null  float64
 23  product_weight_g               113105 non-null  float64
 24  product_length_cm              113105 non-null  float64
 25  product_height_cm              113105 non-null  float64
 26  product_width_cm               113105 non-null  float64
 27  order_item_id                  113105 non-null  int64
 28  seller_id                      113105 non-null  object
 29  shipping_limit_date            113105 non-null  object
 30  price                          113105 non-null  float64
 31  freight_value                  113105 non-null  float64
 32  zip_code_prefix_seller         113105 non-null  int64
 33  lat_seller                     113105 non-null  float64
 34  lng_seller                     113105 non-null  float64
 35  seller_city                    113105 non-null  object
 36  seller_state                   113105 non-null  object
 37  product_category_name          113105 non-null  object
 38  estimated_time                 113105 non-null  float64
 39  actual_time                    113105 non-null  float64
 40  diff_actual_estimated          113105 non-null  float64
 41  diff_purchased_approved        113105 non-null  float64
 42  diff_purchased_courrier        113105 non-null  float64
 43  distance                       113105 non-null  float64
 44  speed                          113105 non-null  float64
 45  same_state                     113105 non-null  int64
 46  same_city                      113105 non-null  int64
 47  late_shipping                  113105 non-null  int64
 48  high_freight                   113105 non-null  int64
 49  seller_share                   113105 non-null  float64
 50  bs_share                       113105 non-null  float64
 51  cust_share                     113105 non-null  float64
 52  bu_share                       113105 non-null  float64
 53  similarity                     113105 non-null  float64
 54  seller_category_share          113105 non-null  float64
 55  cat_seller_share               113105 non-null  float64
 56  cust_category_share            113105 non-null  float64
 57  cat_cust_share                 113105 non-null  float64
 58  similarity_using_cat           113105 non-null  float64
 59  size                           113105 non-null  float64
 60  delivery_day                   113105 non-null  int64
 61  delivery_date                  113105 non-null  int64
 62  delivery_month                 113105 non-null  int64
 63  delivery_hour                  113105 non-null  int64
 64  purchased_day                  113105 non-null  int64
 65  purchased_date                 113105 non-null  int64
 66  purchased_month                113105 non-null  int64
 67  purchased_hour                 113105 non-null  int64
 68  num_of_customers_for_seller    113105 non-null  float64
```

```
 69  num_of_sellers_for_cust          113105 non-null  float64
 70  total_order_for_seller           113105 non-null  float64
dtypes: float64(35), int64(18), object(18)
memory usage: 61.3+ MB
```

In [4]:
```
#label encoding of seller_id
label = LabelEncoder()
seller = label.fit_transform(data.seller_id)
data["seller_id"] = seller


#label encoding of product id
label = LabelEncoder()
product = label.fit_transform(data.product_id)
data["product_id"] = product
```

In [5]:
```
#let us drop some of the columns which are not needed
data.drop(["order_id","customer_id","order_status","order_approved_at","order_delivered_carrier_date",
           "order_estimated_delivery_date","order_delivered_customer_date","customer_unique_id","customer_
          "seller_city","shipping_limit_date","seller_state","customer_state",
           "order_purchase_timestamp"],inplace=True,axis=1)
```

In [6]:
```
#shape of the data after dropping unnecessary columns
data.shape
```

Out[6]:
```
(113105, 57)
```

In [7]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 113105 entries, 0 to 113104
Data columns (total 57 columns):
 #   Column                         Non-Null Count   Dtype  
---  ------                         --------------   -----  
 0   payment_sequential             113105 non-null  int64  
 1   payment_type                   113105 non-null  object 
 2   payment_installments           113105 non-null  int64  
 3   payment_value                  113105 non-null  float64
 4   review_score                   113105 non-null  int64  
 5   zip_code_prefix_customer       113105 non-null  int64  
 6   lat_customer                   113105 non-null  float64
 7   lng_customer                   113105 non-null  float64
 8   product_id                     113105 non-null  int32  
 9   product_name_lenght            113105 non-null  float64
 10  product_description_lenght     113105 non-null  float64
 11  product_photos_qty             113105 non-null  float64
 12  product_weight_g               113105 non-null  float64
 13  product_length_cm              113105 non-null  float64
 14  product_height_cm              113105 non-null  float64
 15  product_width_cm               113105 non-null  float64
 16  order_item_id                  113105 non-null  int64  
 17  seller_id                      113105 non-null  int32  
 18  price                          113105 non-null  float64
 19  freight_value                  113105 non-null  float64
 20  zip_code_prefix_seller         113105 non-null  int64  
 21  lat_seller                     113105 non-null  float64
 22  lng_seller                     113105 non-null  float64
 23  product_category_name          113105 non-null  object 
 24  estimated_time                 113105 non-null  float64
 25  actual_time                    113105 non-null  float64
 26  diff_actual_estimated          113105 non-null  float64
 27  diff_purchased_approved        113105 non-null  float64
 28  diff_purchased_courrier        113105 non-null  float64
 29  distance                       113105 non-null  float64
 30  speed                          113105 non-null  float64
 31  same_state                     113105 non-null  int64  
 32  same_city                      113105 non-null  int64  
 33  late_shipping                  113105 non-null  int64  
 34  high_freight                   113105 non-null  int64  
 35  seller_share                   113105 non-null  float64
 36  bs_share                       113105 non-null  float64
 37  cust_share                     113105 non-null  float64
 38  bu_share                       113105 non-null  float64
 39  similarity                     113105 non-null  float64
 40  seller_category_share          113105 non-null  float64
 41  cat_seller_share               113105 non-null  float64
 42  cust_category_share            113105 non-null  float64
 43  cat_cust_share                 113105 non-null  float64
 44  similarity_using_cat           113105 non-null  float64
 45  size                           113105 non-null  float64
 46  delivery_day                   113105 non-null  int64  
 47  delivery_date                  113105 non-null  int64  
 48  delivery_month                 113105 non-null  int64  
 49  delivery_hour                  113105 non-null  int64  
 50  purchased_day                  113105 non-null  int64  
 51  purchased_date                 113105 non-null  int64  
 52  purchased_month                113105 non-null  int64  
 53  purchased_hour                 113105 non-null  int64  
 54  num_of_customers_for_seller    113105 non-null  float64
 55  num_of_sellers_for_cust        113105 non-null  float64
 56  total_order_for_seller         113105 non-null  float64
dtypes: float64(35), int32(2), int64(18), object(2)
memory usage: 48.3+ MB
```

1.1 Stratified Splitting

In [8]:
```
#target variable is review_score
Y = data["review_score"]
X = data
```

In [9]:
```
#train test split with test size 25% and 75% of data as train
x_train,x_test,y_train,y_test = train_test_split(X,Y,test_size=0.25,stratify=Y,random_state=10)
```

In [10]:
```
print("Dimensions of the splitted data :")
print("Train: ",x_train.shape,y_train.shape)
print("Test: ",x_test.shape,y_test.shape)
```

```
Dimensions of the splitted data :
Train:  (84828, 57) (84828,)
Test:  (28277, 57) (28277,)
```

In [11]:
```
#check the distribution of each class in train,test as well as original data
print("% Distribution of class labels in the total data :")
print(round(data["review_score"].value_counts(normalize=True)*100,2))
print("*"*50)

print("% Distribution of class labels in the train data :")
print(round(x_train["review_score"].value_counts(normalize=True)*100,2))
print("*"*50)

print("% Distribution of class labels in the test data :")
print(round(x_test["review_score"].value_counts(normalize=True)*100,2))
print("*"*50)
```

```
% Distribution of class labels in the total data :
5    57.15
4    19.21
1    11.71
3     8.46
2     3.47
Name: review_score, dtype: float64
**************************************************
% Distribution of class labels in the train data :
5    57.15
4    19.21
1    11.71
3     8.46
2     3.47
Name: review_score, dtype: float64
**************************************************
% Distribution of class labels in the test data :
5    57.15
4    19.21
1    11.71
3     8.46
2     3.47
Name: review_score, dtype: float64
**************************************************
```

- Distribution of each class label is same in train.test and original data.

Data is highly imbalanced. % of class 2 is very less. So we might face problem of misclassification due to this imbalanced data. Before applying any advanced techniques, let us build simple models and check how model will perform with this data.

let us use simple CountVectorizer for categorical data.

1.2 Featurization:

1.2.1 Vectorization of categorical variables:

In [12]:
```
from sklearn.feature_extraction.text import CountVectorizer
```

1. payment_type

In [13]:
```
#payment_type
vec = CountVectorizer()

vec.fit(x_train["payment_type"].values)

x_tr_pay_type = vec.transform(x_train.payment_type.values)
x_te_pay_type = vec.transform(x_test.payment_type.values)

print(x_tr_pay_type.shape)
print(x_te_pay_type.shape)
```

```
(84828, 4)
(28277, 4)
```

2. order_item_id

In [16]:
```
x_train.order_item_id = x_train.order_item_id.astype(str)
x_test.order_item_id = x_test.order_item_id.astype(str)
```

In [17]:
```
#order_item_id
vec = CountVectorizer(vocabulary=range(1,22))

vec.fit(x_train["order_item_id"])

x_tr_id = vec.transform(x_train.order_item_id)
x_te_id = vec.transform(x_test.order_item_id)

print(x_tr_id.shape)

print(x_te_id.shape)
```

```
(84828, 21)
(28277, 21)
```

3. product_category_name

In [18]:
```
#product_category_name
vec = CountVectorizer()

vec.fit(x_train["product_category_name"].values)

x_tr_cat = vec.transform(x_train.product_category_name.values)
#x_cv_cat = vec.transform(x_cv.product_category_name.values).toarray()
x_te_cat = vec.transform(x_test.product_category_name.values)

print(x_tr_cat.shape)
#print(x_cv_cat.shape)
print(x_te_cat.shape)
```

```
(84828, 73)
(28277, 73)
```

In [ ]:
```

```

1.2.2 Binary features

In [19]:
```
x_tr_same_state = x_train.same_state.values.reshape(-1,1)
x_te_same_state = x_test.same_state.values.reshape(-1,1)

x_tr_same_city = x_train.same_city.values.reshape(-1,1)
x_te_same_city = x_test.same_city.values.reshape(-1,1)

x_tr_late_shipping = x_train.late_shipping.values.reshape(-1,1)
x_te_late_shipping = x_test.late_shipping.values.reshape(-1,1)

x_tr_high_freight = x_train.high_freight.values.reshape(-1,1)
x_te_high_freight = x_test.high_freight.values.reshape(-1,1)
```

1.2.3 Numrical features

In [20]:
```

def scaling(train_data,test_data):
    """This function will standardize the numerical data"""
    norm = StandardScaler()

    norm.fit(train_data.values)

    x_tr_num = norm.transform(train_data.values)
    x_te_num = norm.transform(test_data.values)


    return x_tr_num,x_te_num
```

In [21]:
```
data.columns
```

Out[21]:
```
Index(['payment_sequential', 'payment_type', 'payment_installments',
       'payment_value', 'review_score', 'zip_code_prefix_customer',
       'lat_customer', 'lng_customer', 'product_id', 'product_name_lenght',
       'product_description_lenght', 'product_photos_qty', 'product_weight_g',
       'product_length_cm', 'product_height_cm', 'product_width_cm',
       'order_item_id', 'seller_id', 'price', 'freight_value',
       'zip_code_prefix_seller', 'lat_seller', 'lng_seller',
       'product_category_name', 'estimated_time', 'actual_time',
       'diff_actual_estimated', 'diff_purchased_approved',
       'diff_purchased_courrier', 'distance', 'speed', 'same_state',
       'same_city', 'late_shipping', 'high_freight', 'seller_share',
       'bs_share', 'cust_share', 'bu_share', 'similarity',
       'seller_category_share', 'cat_seller_share', 'cust_category_share',
       'cat_cust_share', 'similarity_using_cat', 'size', 'delivery_day',
       'delivery_date', 'delivery_month', 'delivery_hour', 'purchased_day',
       'purchased_date', 'purchased_month', 'purchased_hour',
       'num_of_customers_for_seller', 'num_of_sellers_for_cust',
       'total_order_for_seller'],
      dtype='object')
```

In [22]:
```
#data to be standardized
tr = x_train[["payment_sequential","payment_installments","payment_value","seller_id","product_id","seller
              "bs_share","cust_share",
          "lat_customer","lng_customer","lat_seller","lng_seller","product_name_lenght","product_descripti
           "product_photos_qty","product_weight_g","size","price","delivery_day","delivery_date","delivery
              "delivery_hour","purchased_day","purchased_date","purchased_month","purchased_hour","num_of_
              "num_of_sellers_for_cust","total_order_for_seller",
           "freight_value","estimated_time","actual_time","diff_actual_estimated","diff_purchased_approved
           "diff_purchased_courrier","distance","speed","similarity","similarity_using_cat"]]

te = x_test[["payment_sequential","payment_installments","payment_value","seller_id","product_id","seller_
              "bs_share","cust_share",
          "lat_customer","lng_customer","lat_seller","lng_seller","product_name_lenght","product_descripti
           "product_photos_qty","product_weight_g","size","price","delivery_day","delivery_date","delivery
              "delivery_hour","purchased_day","purchased_date","purchased_month","purchased_hour","num_of_
              "num_of_sellers_for_cust","total_order_for_seller",
           "freight_value","estimated_time","actual_time","diff_actual_estimated","diff_purchased_approved
           "diff_purchased_courrier","distance","speed","similarity","similarity_using_cat"]]
```

In [23]:
```
#standardizing
x_tr_num,x_te_num = scaling(tr,te)
```

In [24]:
```
from scipy.sparse import hstack
#horizontal stacking of all the features
train = hstack((x_tr_pay_type,x_tr_id,x_tr_cat,x_tr_num,x_tr_same_state,
                   x_tr_same_city,x_tr_late_shipping,x_tr_high_freight)).toarray()

test = hstack((x_te_pay_type,x_te_id,x_te_cat,x_te_num,x_te_same_state,
                 x_te_same_city,x_te_late_shipping,x_te_high_freight)).toarray()
```

In [25]:
```
#shape of final train and test data
print("Shape of train data : ",train.shape)
print("Shape of test data : ",test.shape)
```

```
Shape of train data :  (84828, 142)
Shape of test data :  (28277, 142)
```

In [26]:
```
#reset the index of target variable
y_trains = y_train.reset_index()
y_train = y_trains["review_score"]

y_tests = y_test.reset_index()
y_test = y_tests["review_score"]
```

In [27]:
```
#saving all the train,test,y_train,y_test data as csv file
pd.DataFrame(train).to_csv("train.csv")
pd.DataFrame(test).to_csv("test.csv")
pd.DataFrame(y_train).to_csv("y_train.csv")
pd.DataFrame(y_test).to_csv("y_test.csv")
```

1.3 ML Models

Plotting Confusion matrix

In [28]:
```
# This function plots the confusion matrices given y_i, y_i_hat.
def plot_confusion_matrix(test_y, predict_y):
    """This function will plot confusion matrix, precision matrix and recall matrix"""
    C = confusion_matrix(test_y, predict_y)
    A =(((C.T)/(C.sum(axis=1))).T)
    B =(C/C.sum(axis=0))

    labels = [1,2,3,4,5]
    # representing A in heatmap format
    print("-"*20, "Confusion matrix", "-"*20)
    plt.figure(figsize=(20,7))
    sns.heatmap(C, annot=True, cmap="YlGnBu", fmt=".3f", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()

    print("-"*20, "Precision matrix (Columm Sum=1)", "-"*20)
    plt.figure(figsize=(20,7))
    sns.heatmap(B, annot=True, cmap="YlGnBu", fmt=".3f", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()

    # representing B in heatmap format
    print("-"*20, "Recall matrix (Row sum=1)", "-"*20)
    plt.figure(figsize=(20,7))
    sns.heatmap(A, annot=True, cmap="YlGnBu", fmt=".3f", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()
```

k-fold cross validation

In [47]:
```
def kfold(k,model,trains,y_trains):
    """This function will do stratified k-fold cross_validation"""
    kf = StratifiedKFold(n_splits=k)

    cv_f1_score = []
    for tr_ind,cv_ind in kf.split(trains,y_trains):

        x_tr,x_cv,y_tr,y_cv = trains[tr_ind],trains[cv_ind],y_trains[tr_ind],y_trains[cv_ind]

        model.fit(x_tr,y_tr)
        pred_cv = model.predict(x_cv)
        cv_f1_score.append((f1_score(y_cv,pred_cv,average="macro",labels=[1,2,3,4,5])))

    return np.mean(cv_f1_score)
```

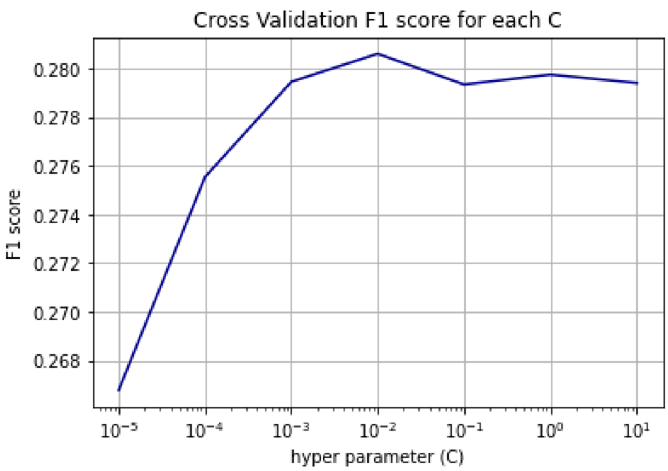
1.3.1 Logistic regression

One vs Rest with class_weight = balanced

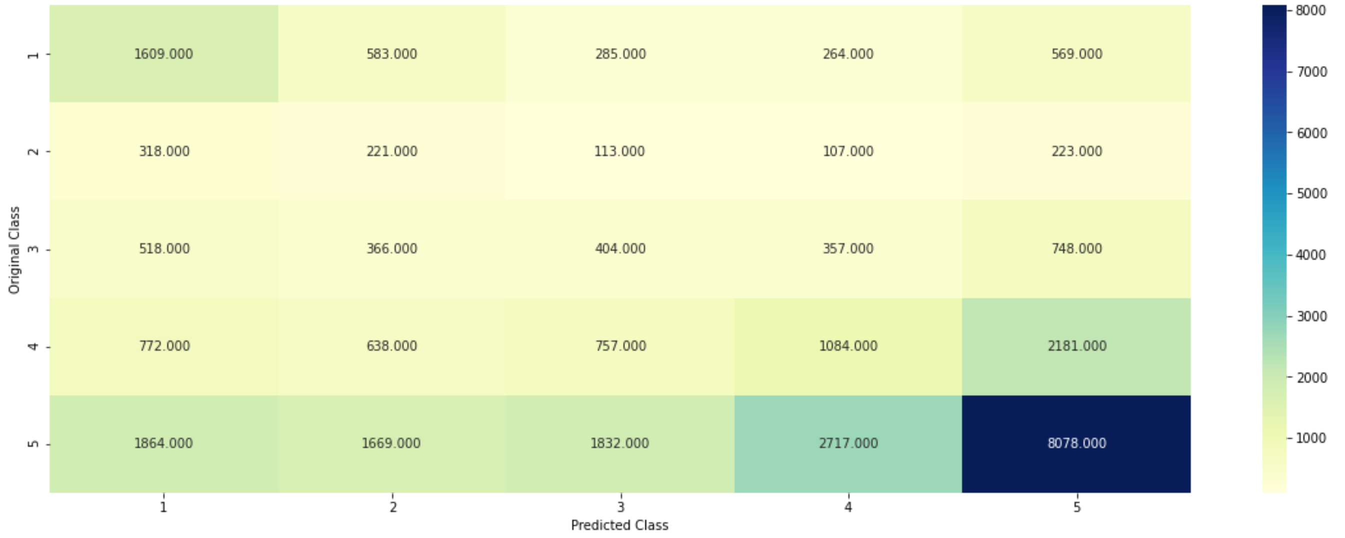
In [30]:

```python
C=[0.00001,0.0001,0.001,0.01,0.1,1,10]

f1_scores = []
for i in C:
    model = None
    model = LogisticRegression(C=i,class_weight="balanced")
    k_fold_score = kfold(5,model)
    f1_scores.append(k_fold_score)
    print("Macro F1 score at C={} is {} ".format(i,k_fold_score))



print("*"*50)
plt.plot(C,f1_scores,color="darkblue")
plt.xscale("log")
plt.grid()
plt.title("Cross Validation F1 score for each C")
plt.xlabel("hyper parameter (C)")
plt.ylabel("F1 score")
plt.show()

best_param = C[np.argmax(f1_scores)]

model = None
model = LogisticRegression(C=i,class_weight="balanced")
model.fit(train,y_train)


print("*"*50)
print("Train F1 score at {} is :{}".format(best_param, f1_score(y_train,model.predict(train),labels=model.
print("*"*50)
print("test F1 score at {} is :{}".format(best_param, f1_score(y_test,model.predict(test),labels=model.cla


#plotting confusion matrix
predicted = model.predict(test)
plot_confusion_matrix(y_test,predicted)
```

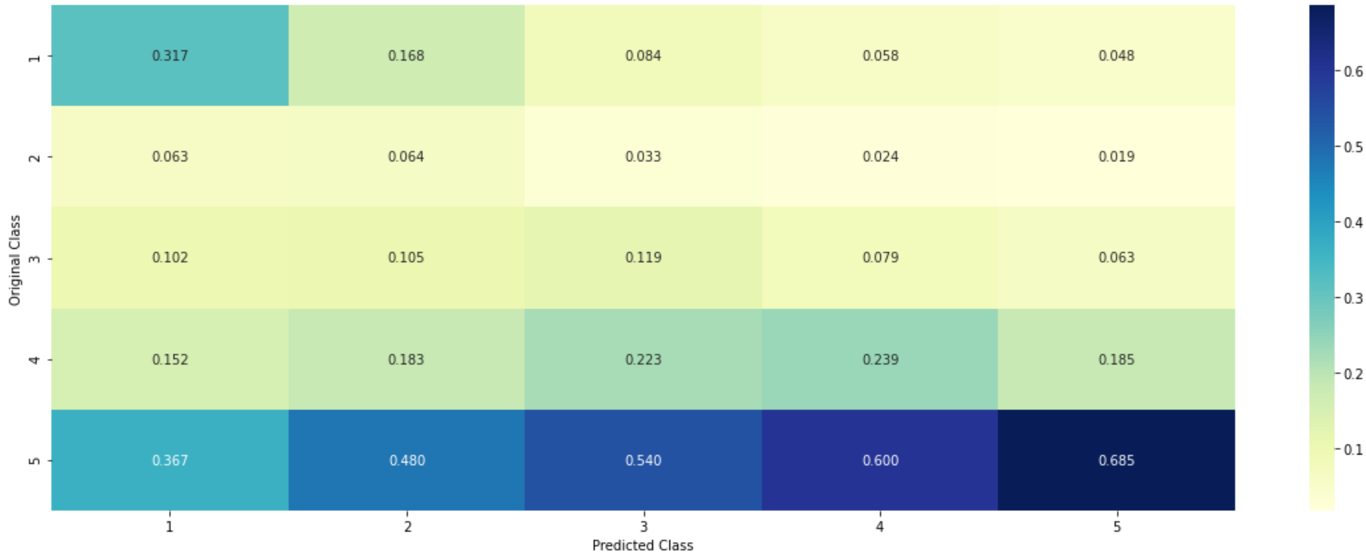
```
Macro F1 score at C=1e-05 is 0.2667786760007065
Macro F1 score at C=0.0001 is 0.2755378965564173
Macro F1 score at C=0.001 is 0.27945397462502053
Macro F1 score at C=0.01 is 0.28060695323811763
Macro F1 score at C=0.1 is 0.2793416309176847
Macro F1 score at C=1 is 0.2797501330074962
Macro F1 score at C=10 is 0.27940265832423244
**************************************************
```



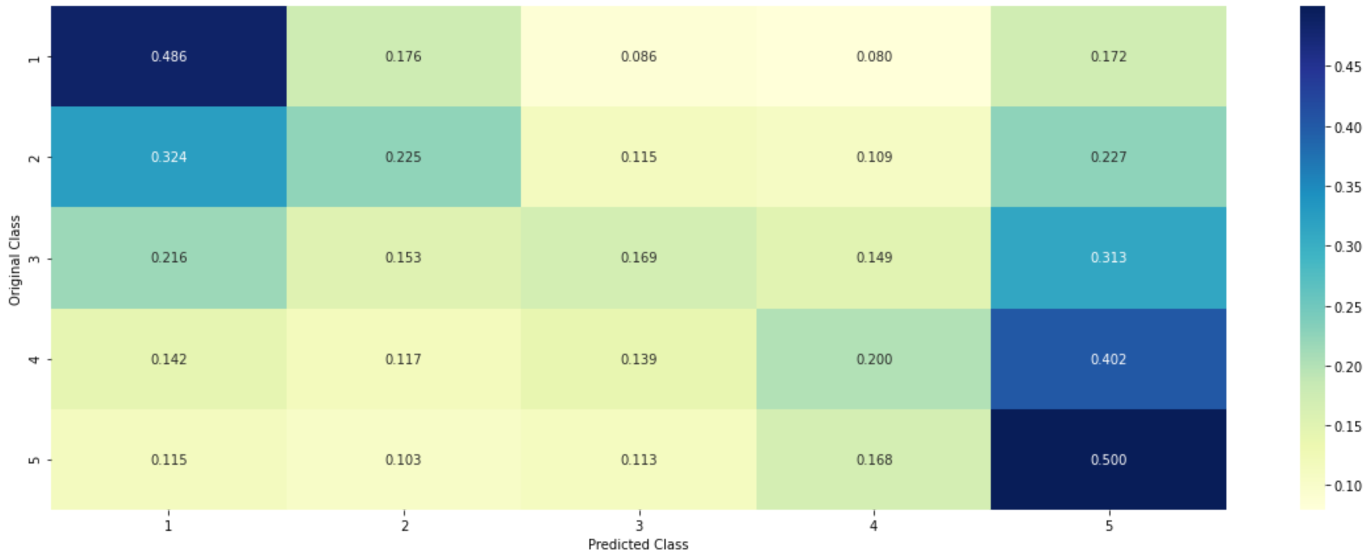

```
**************************************************
Train F1 score at 0.01 is :0.2859309445799382
**************************************************
test F1 score at 0.01 is :0.28356443530884495
-------------------- Confusion matrix --------------------
```



------------------- Precision matrix (Columm Sum=1) -------------------



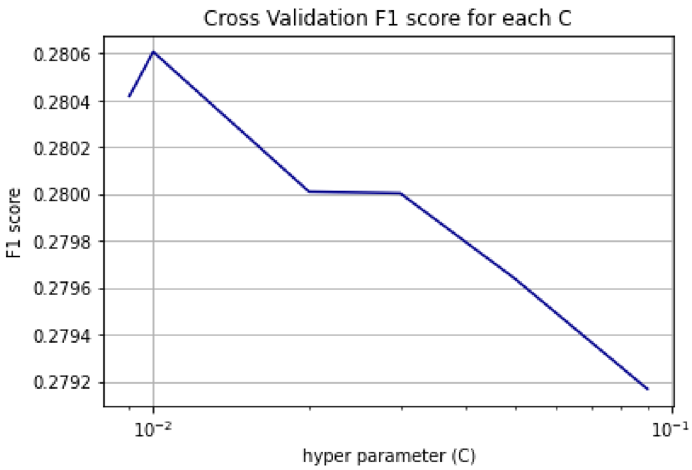
------------------- Recall matrix (Row sum=1) -------------------



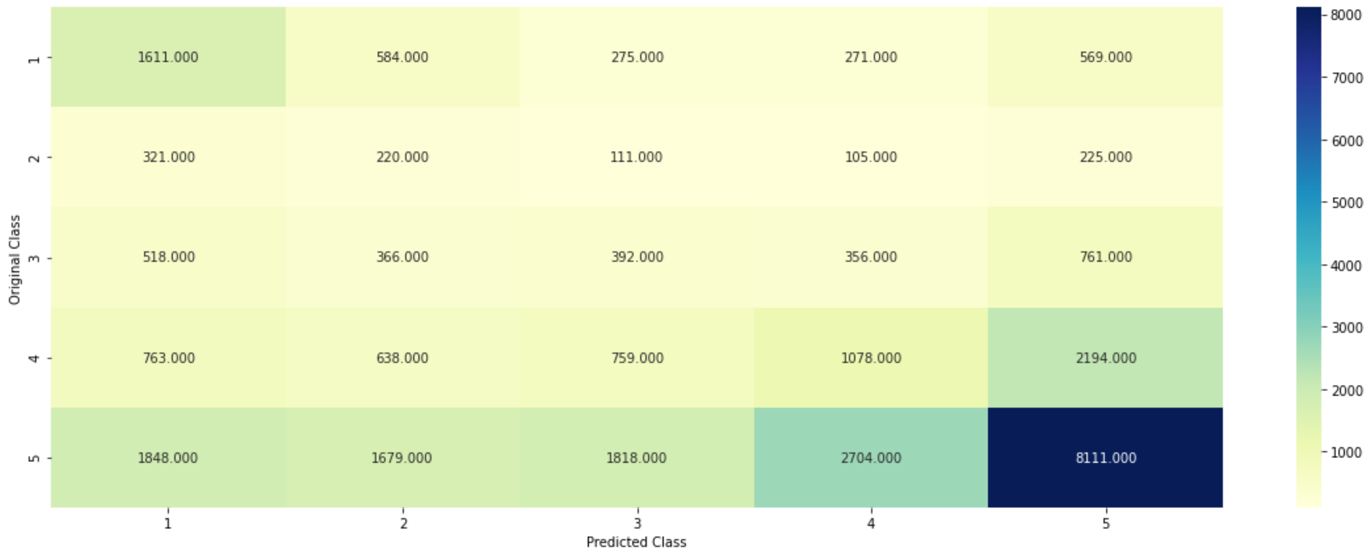
In [33]:

```
C=[0.009,0.01,0.02,0.03,0.05,0.09]

f1_scores = []
for i in C:
    model = None
    model = LogisticRegression(C=i,class_weight="balanced")
    k_fold_score = kfold(5,model)
    f1_scores.append(k_fold_score)
    print("Macro F1 score at C={} is {} ".format(i,k_fold_score))



print("*"*50)
plt.plot(C,f1_scores,color="darkblue")
#plt.xscale("log")
plt.grid()
plt.title("Cross Validation F1 score for each C")
plt.xlabel("hyper parameter (C)")
plt.ylabel("F1 score")
plt.show()

best_param = C[np.argmax(f1_scores)]

model = None
model = LogisticRegression(C=i,class_weight="balanced")
model.fit(train,y_train)


print("*"*50)
print("Train F1 score at {} is :{}".format(best_param, f1_score(y_train,model.predict(train),labels=model.
print("*"*50)
print("test F1 score at {} is :{}".format(best_param, f1_score(y_test,model.predict(test),labels=model.cla


#plotting confusion matrix
predicted = model.predict(test)
plot_confusion_matrix(y_test,predicted)
```

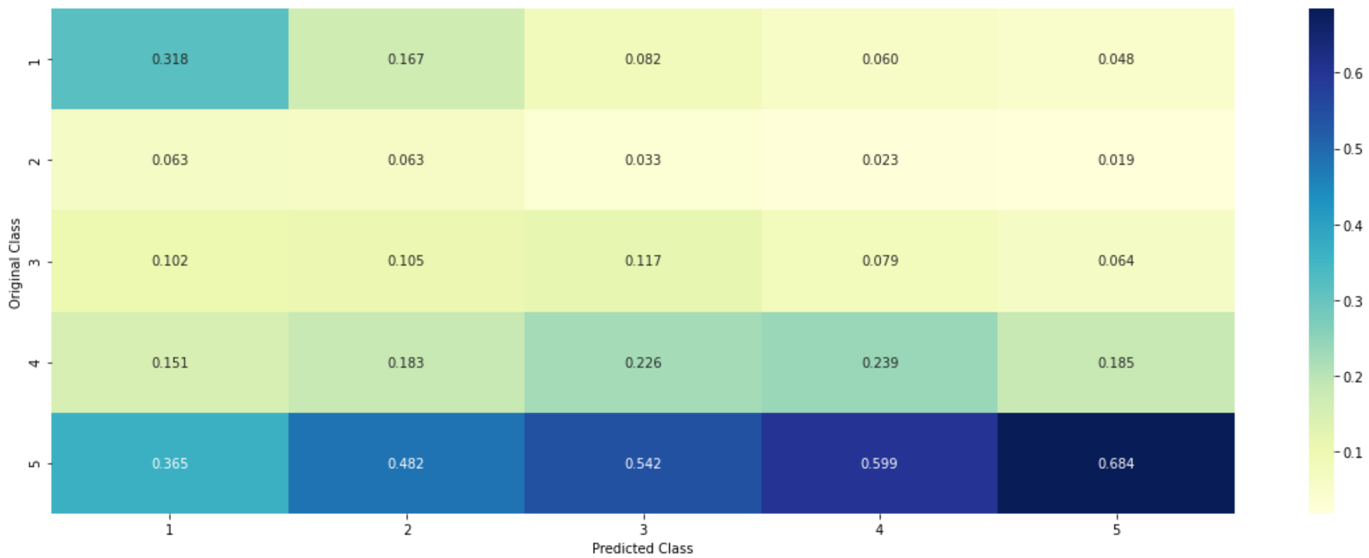
```
Macro F1 score at C=0.009 is 0.2804181734297707
Macro F1 score at C=0.01 is 0.28060695323811763
Macro F1 score at C=0.02 is 0.2800099384943631
Macro F1 score at C=0.03 is 0.28000319502996324
Macro F1 score at C=0.05 is 0.2796378261604237
Macro F1 score at C=0.09 is 0.2791679732793583
**************************************************
```



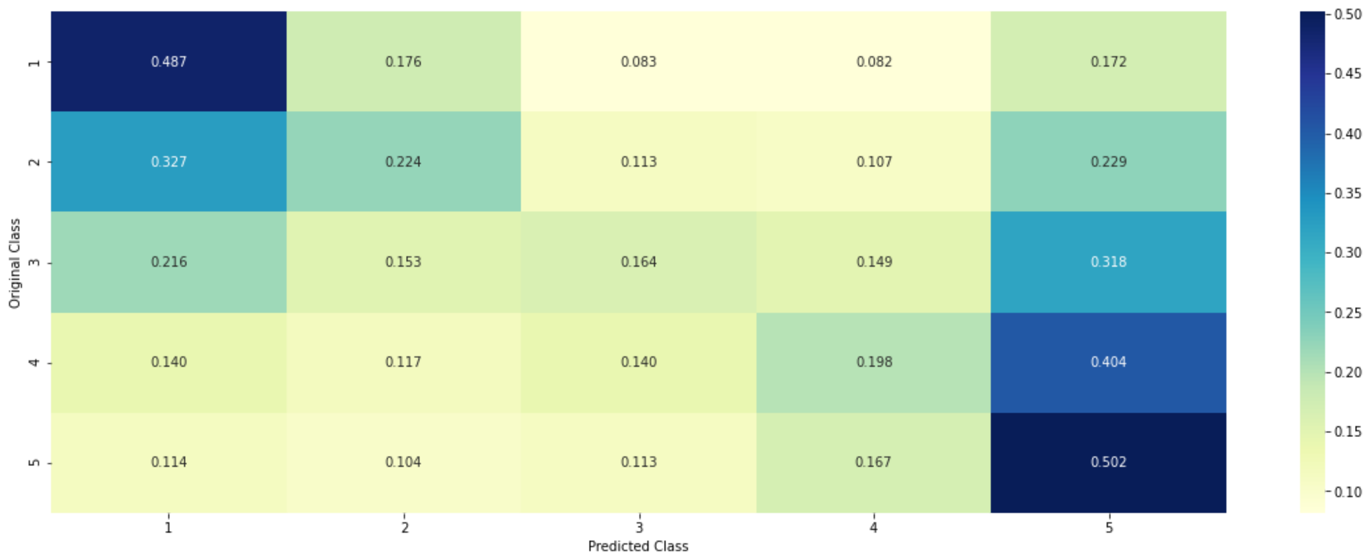
```
**************************************************
Train F1 score at 0.01 is :0.2861436760880077
**************************************************
test F1 score at 0.01 is :0.2830931443905419
-------------------- Confusion matrix --------------------
```




```
-------------------- Precision matrix (Columm Sum=1) --------------------
```



-------------------- Recall matrix (Row sum=1) --------------------



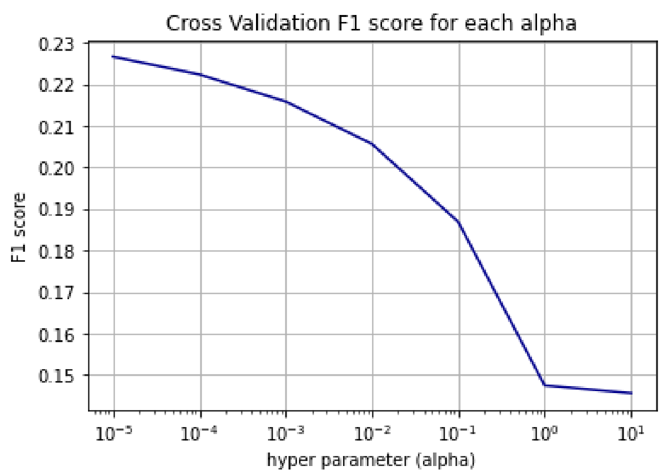
- First I tried simple logistic regression to check whether the data is linearly separable or not.
- But we don't get good results from this model.
- The performance of this model is not at all good. There are high misclassification, and macro f1 score is very less.
- Out of all review_score 5 only 50% of points are correctly predicted as class 5.
- Out of all class 5 classified points only 68% are actually class 5.
- This misclassification problem is there in all class labels.
- Precision and recall of class label 2,3 are very low.
- So, the data seems to be not linearly separable.

1.3.2 SVM

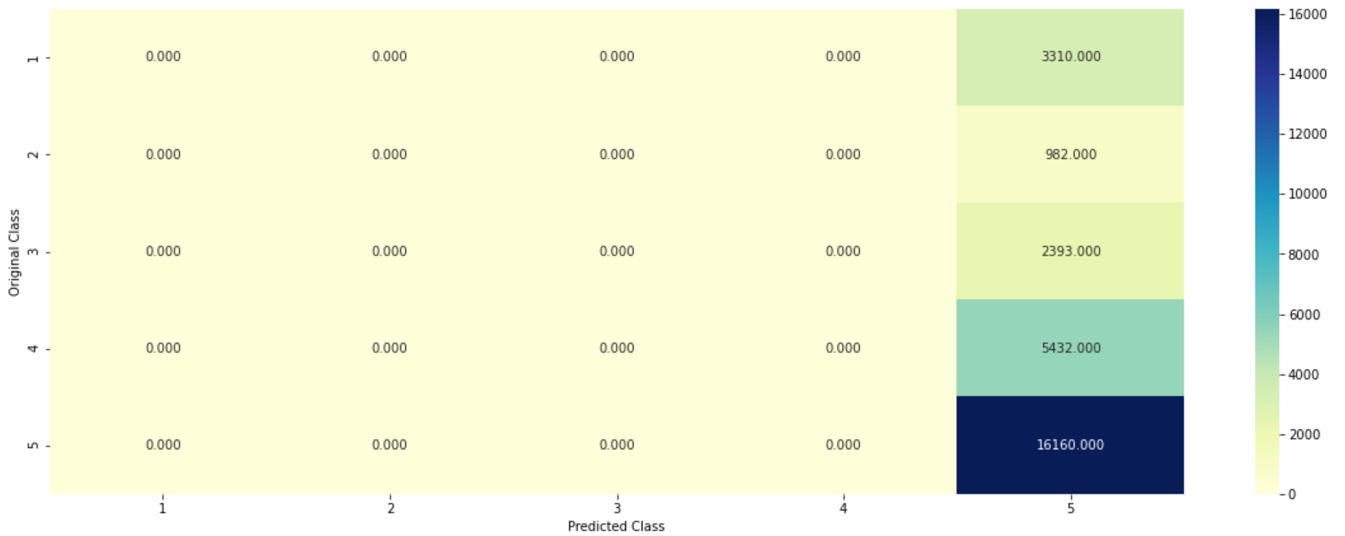
In [32]:

```
alpha=[0.00001,0.0001,0.001,0.01,0.1,1,10]

f1_scores = []
for i in alpha:
    model = None
    model = SGDClassifier(alpha=i,loss="hinge")
    k_fold_score = kfold(5,model)
    f1_scores.append(k_fold_score)
    print("Macro F1 score at alpha={} is {} ".format(i,k_fold_score))



print("*"*50)
plt.plot(alpha,f1_scores,color="darkblue")
plt.xscale("log")
plt.grid()
plt.title("Cross Validation F1 score for each alpha")
plt.xlabel("hyper parameter (alpha)")
plt.ylabel("F1 score")
plt.show()

best_param = alpha[np.argmax(f1_scores)]

model = None
model = SGDClassifier(alpha=i,loss="hinge")
model.fit(train,y_train)


print("*"*50)
print("Train F1 score at {} is :{}".format(best_param, f1_score(y_train,model.predict(train),labels=model.
print("*"*50)
print("test F1 score at {} is :{}".format(best_param, f1_score(y_test,model.predict(test),labels=model.cla


#plotting confusion matrix
predicted = model.predict(test)
plot_confusion_matrix(y_test,predicted)
```

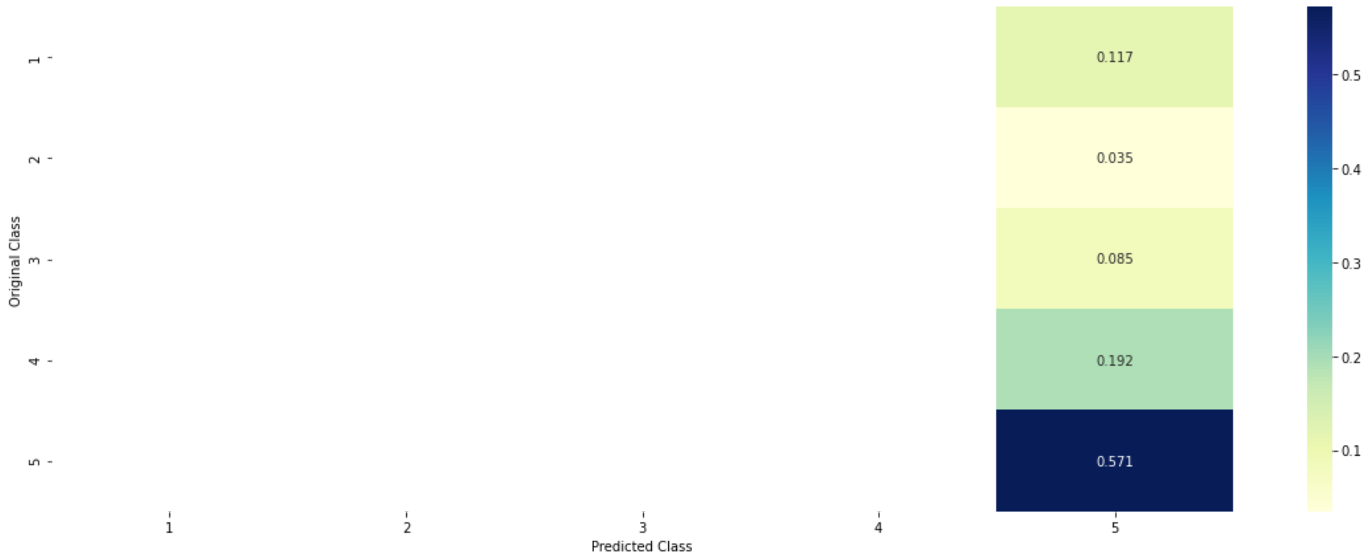
```
Macro F1 score at alpha=1e-05 is 0.22667955962631292
Macro F1 score at alpha=0.0001 is 0.2224246339809955
Macro F1 score at alpha=0.001 is 0.21587831678954625
Macro F1 score at alpha=0.01 is 0.20566121048715855
Macro F1 score at alpha=0.1 is 0.18686707882280684
Macro F1 score at alpha=1 is 0.1474467601768059
Macro F1 score at alpha=10 is 0.14554671810346959
**************************************************
```



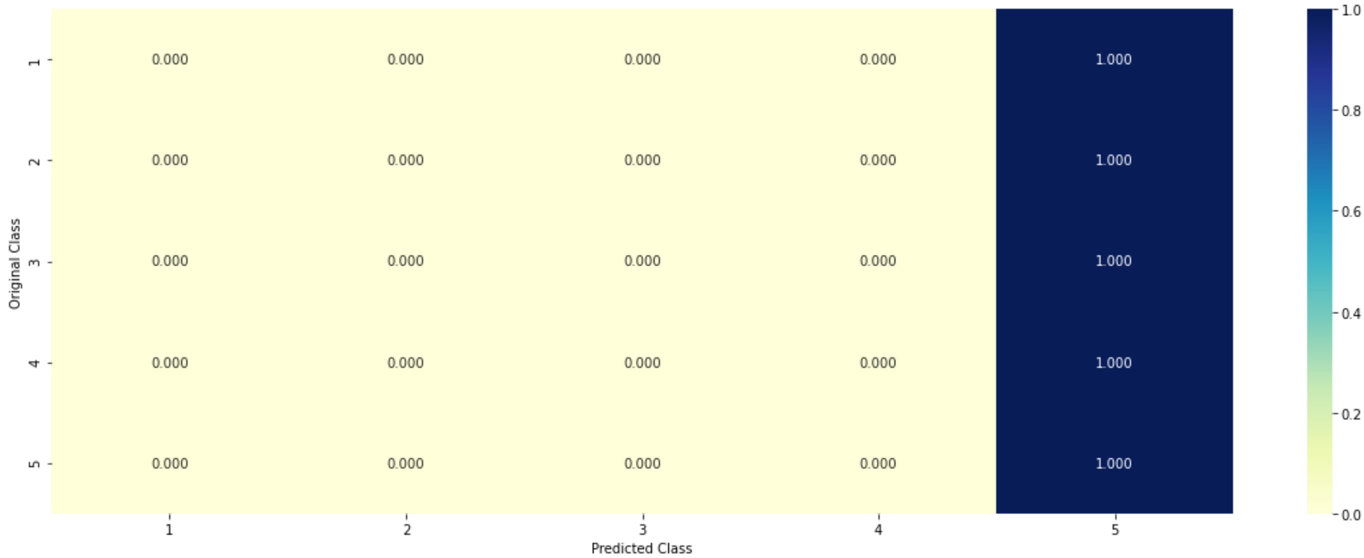

```
**************************************************
Train F1 score at 1e-05 is :0.1455032757226727
**************************************************
test F1 score at 1e-05 is :0.14546436528118462
-------------------- Confusion matrix --------------------
```




```
------------------- Precision matrix (Columm Sum=1) -------------------
```




```
------------------- Recall matrix (Row sum=1) --------------------
```



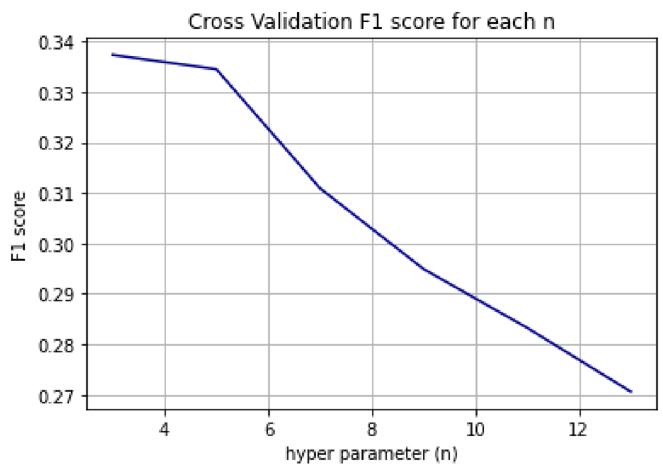
- This is worst model.
- It classifies every point as class 5.
- SVM is not able to distinguish among classes.

1.3.3 KNN

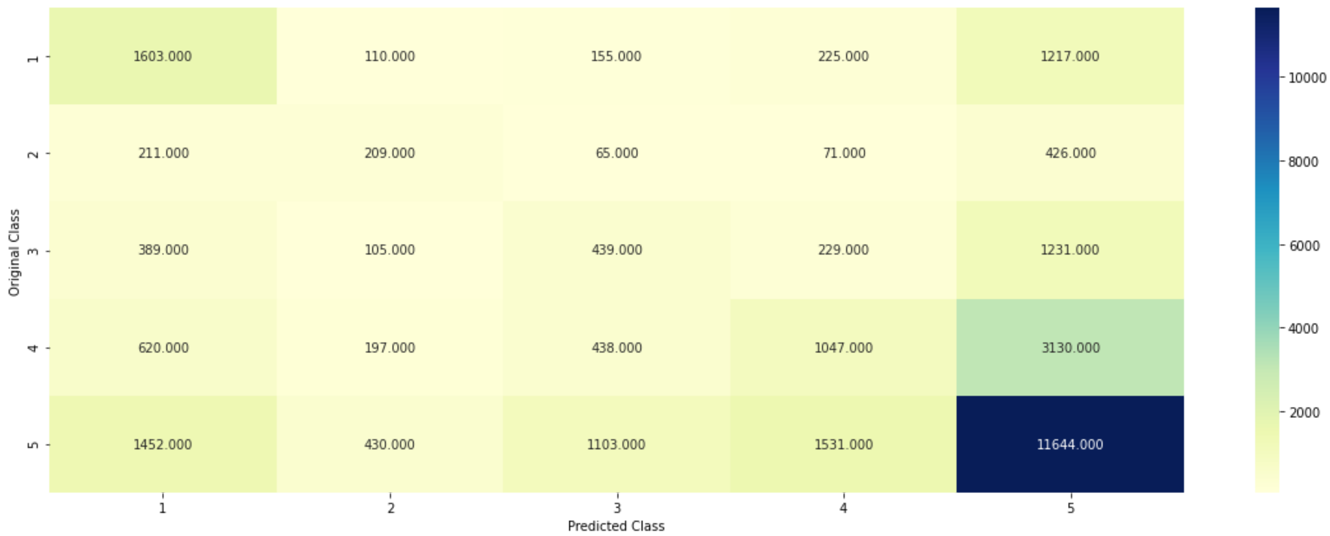
In [31]:
```
from sklearn.neighbors import KNeighborsClassifier
```

In [32]:
```
n=[3,5,7,9,11,13]

f1_scores = []
for i in n:
    model = None
    model = KNeighborsClassifier(n_neighbors=i)
    k_fold_score = kfold(5,model)
    f1_scores.append(k_fold_score)
    print("Macro F1 score at n={} is {} ".format(i,k_fold_score))



print("*"*50)
plt.plot(n,f1_scores,color="darkblue")

plt.grid()
plt.title("Cross Validation F1 score for each n")
plt.xlabel("hyper parameter (n)")
plt.ylabel("F1 score")
plt.show()

best_param = n[np.argmax(f1_scores)]

model = None
model = KNeighborsClassifier(n_neighbors=best_param)
model.fit(train,y_train)


print("*"*50)
print("Train F1 score at {} is :{}".format(best_param, f1_score(y_train,model.predict(train),labels=model.
print("*"*50)
print("test F1 score at {} is :{}".format(best_param, f1_score(y_test,model.predict(test),labels=model.cla


#plotting confusion matrix
predicted = model.predict(test)
plot_confusion_matrix(y_test,predicted)
```

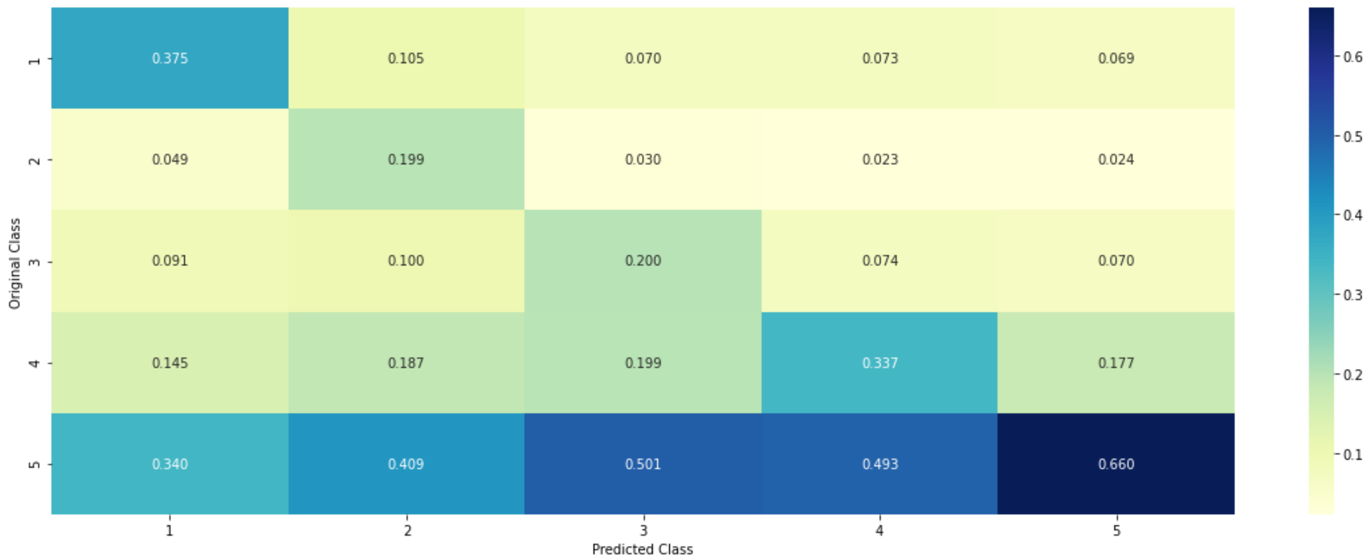
```
Macro F1 score at n=3 is 0.33731364999563346
Macro F1 score at n=5 is 0.3345040369305531
Macro F1 score at n=7 is 0.3109171442984063
Macro F1 score at n=9 is 0.29489979526225596
Macro F1 score at n=11 is 0.28326470501836726
Macro F1 score at n=13 is 0.2706057850190862
**************************************************
```



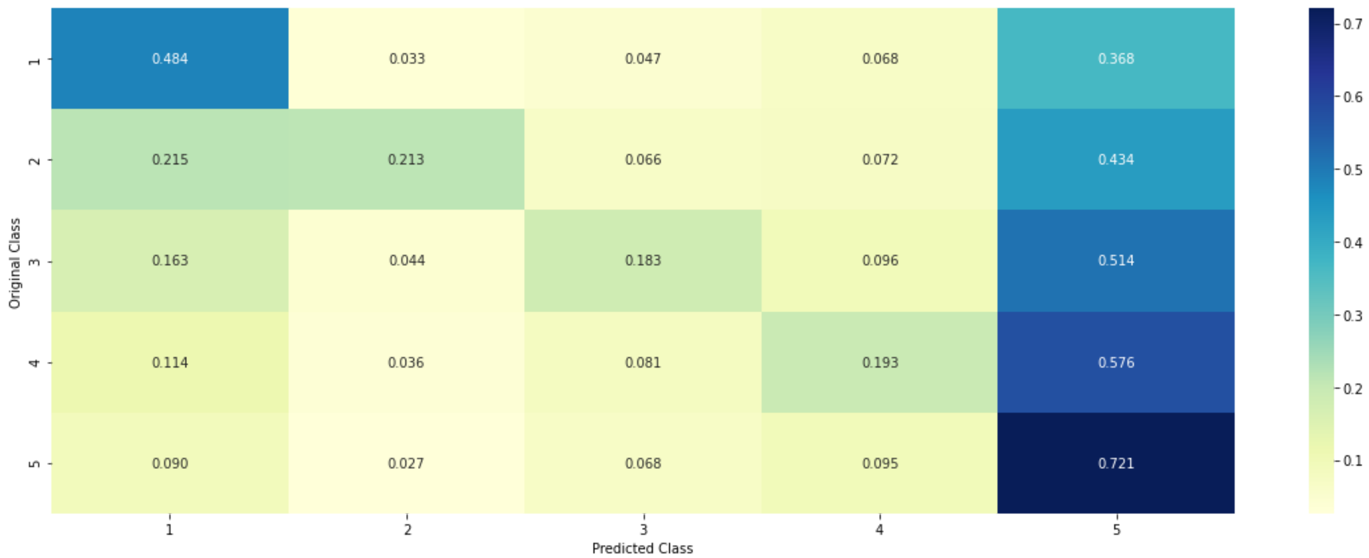

```
**************************************************
Train F1 score at 3 is :0.6482092305976689
**************************************************
test F1 score at 3 is :0.3507236050975718
-------------------- Confusion matrix --------------------
```




```
------------------- Precision matrix (Columm Sum=1) -------------------
```




```
------------------- Recall matrix (Row sum=1) -------------------
```



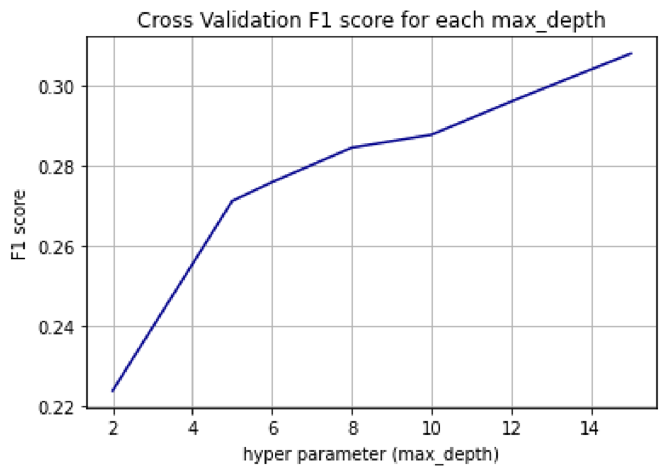
- This model seems to be little bit overfitting.
- Precision as well as recall of class 2,3,4 are better than logistic regression results.
- But we need very high recall for class 1,2,3. Also high precision for class 4 and 5. We need to improve this.

1.3.4. Decision Tree

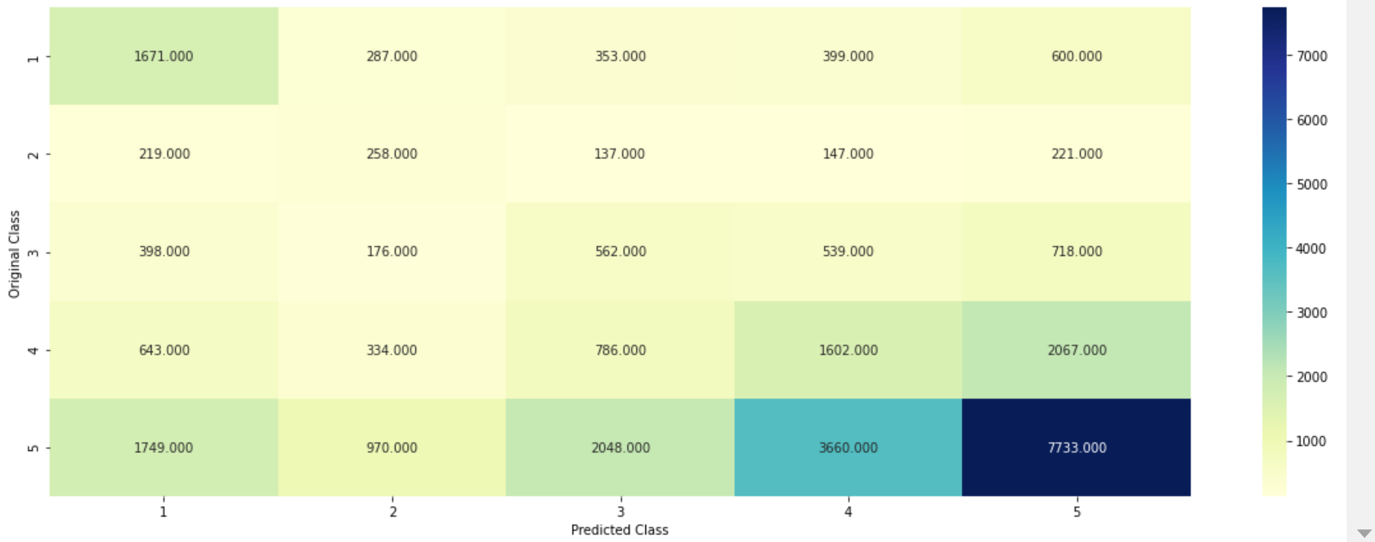
In [34]:
```
from sklearn.tree import DecisionTreeClassifier
```

In [35]:
```
max_depth=[2,5,6,8,10,12,15]

f1_scores = []
for i in max_depth:
    model = None
    model = DecisionTreeClassifier(max_depth=i,class_weight="balanced")
    k_fold_score = kfold(5,model)
    f1_scores.append(k_fold_score)
    print("Macro F1 score at n={} is {} ".format(i,k_fold_score))



print("*"*50)
plt.plot(max_depth,f1_scores,color="darkblue")

plt.grid()
plt.title("Cross Validation F1 score for each max_depth")
plt.xlabel("hyper parameter (max_depth)")
plt.ylabel("F1 score")
plt.show()

best_param = max_depth[np.argmax(f1_scores)]

model = None
model = DecisionTreeClassifier(max_depth=best_param,class_weight="balanced")
model.fit(train,y_train)


print("*"*50)
print("Train F1 score at {} is :{}".format(best_param, f1_score(y_train,model.predict(train),labels=model.
print("*"*50)
print("test F1 score at {} is :{}".format(best_param, f1_score(y_test,model.predict(test),labels=model.cla


#plotting confusion matrix
predicted = model.predict(test)
plot_confusion_matrix(y_test,predicted)
```

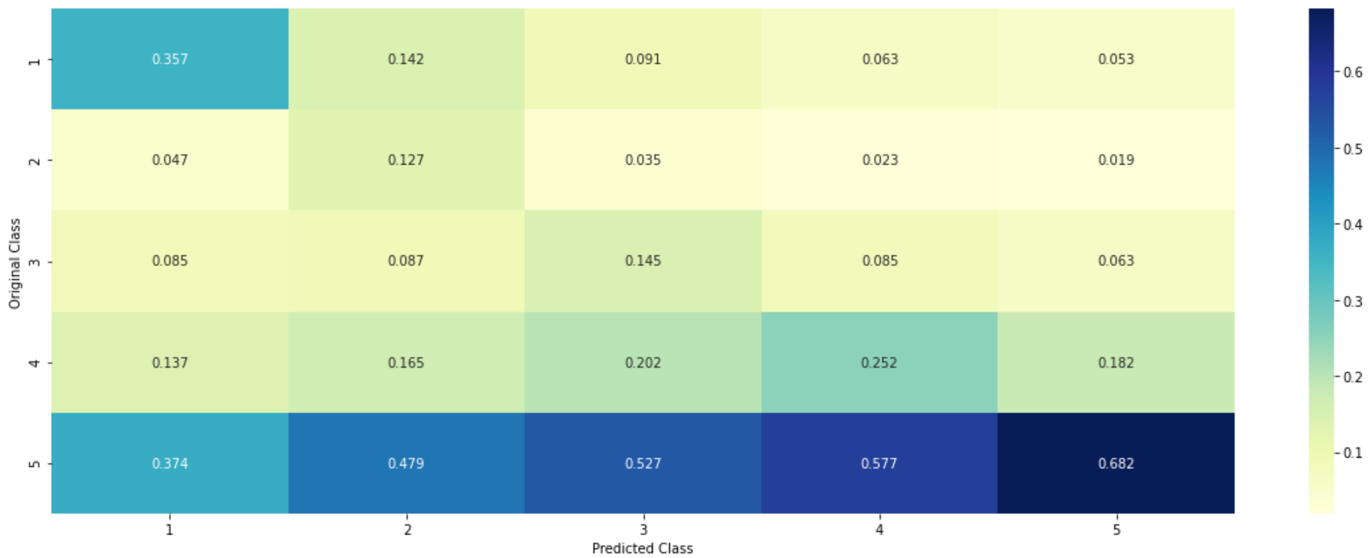
```
Macro F1 score at n=2 is 0.2239007983602522
Macro F1 score at n=5 is 0.2711927629949459
Macro F1 score at n=6 is 0.2758960078341464
Macro F1 score at n=8 is 0.2844841878704538
Macro F1 score at n=10 is 0.2877129470699218
Macro F1 score at n=12 is 0.29600247646173894
Macro F1 score at n=15 is 0.3079512516658536
**************************************************
```



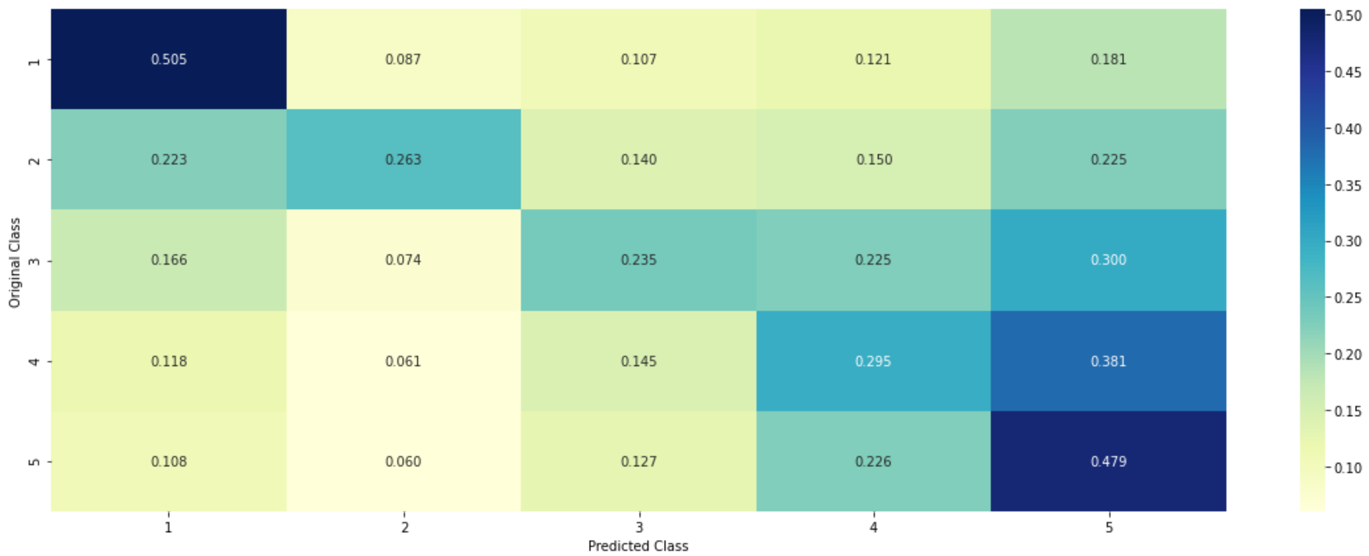

```
**************************************************
Train F1 score at 15 is :0.44340009830874527
**************************************************
test F1 score at 15 is :0.3206623596966399
-------------------- Confusion matrix --------------------
```




```
------------------- Precision matrix (Columm Sum=1) -------------------
```




```
------------------- Recall matrix (Row sum=1) -------------------
```



In [ ]:

- This model also seems little overfitted. But recall of class 2,3,4 has imrpoved compared to previous models.
- Let us build Random Forest and will see the performance

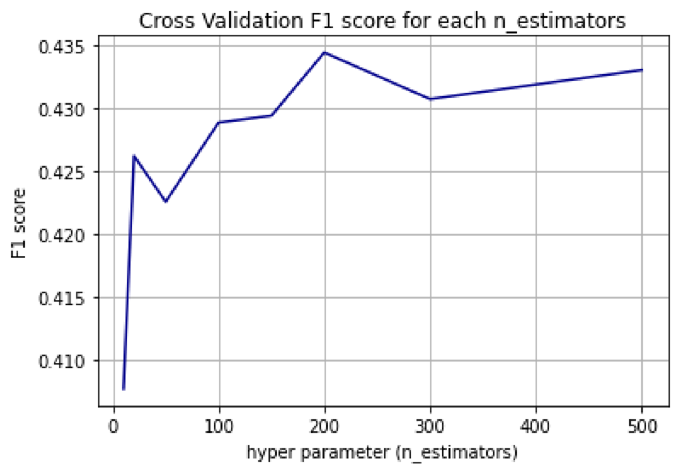
1.3.5. Random Forest classifier

In [39]:

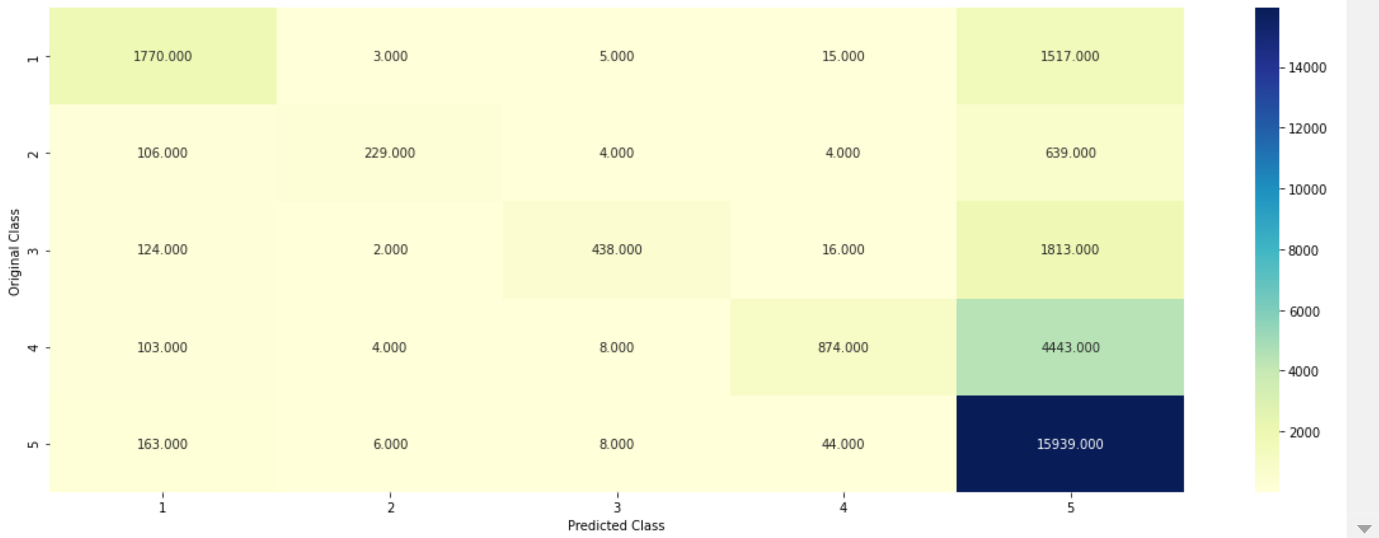
```
from sklearn.ensemble import RandomForestClassifier
```

In [40]:
```
n_estimators=[10,20,50,100,150,200,300,500]


f1_scores = []
for i in n_estimators:
    model = None
    model = RandomForestClassifier(n_estimators=i)
    k_fold_score = kfold(5,model)
    f1_scores.append(k_fold_score)
    print("Macro F1 score at n={} is {} ".format(i,k_fold_score))



print("*"*50)
plt.plot(n_estimators,f1_scores,color="darkblue")

plt.grid()
plt.title("Cross Validation F1 score for each n_estimators")
plt.xlabel("hyper parameter (n_estimators)")
plt.ylabel("F1 score")
plt.show()

best_param = n_estimators[np.argmax(f1_scores)]

model = None
model = RandomForestClassifier(n_estimators=best_param)
model.fit(train,y_train)


print("*"*50)
print("Train F1 score at {} is :{}".format(best_param, f1_score(y_train,model.predict(train),labels=model.
print("*"*50)
print("test F1 score at {} is :{}".format(best_param, f1_score(y_test,model.predict(test),labels=model.cla


#plotting confusion matrix
predicted = model.predict(test)
plot_confusion_matrix(y_test,predicted)
```

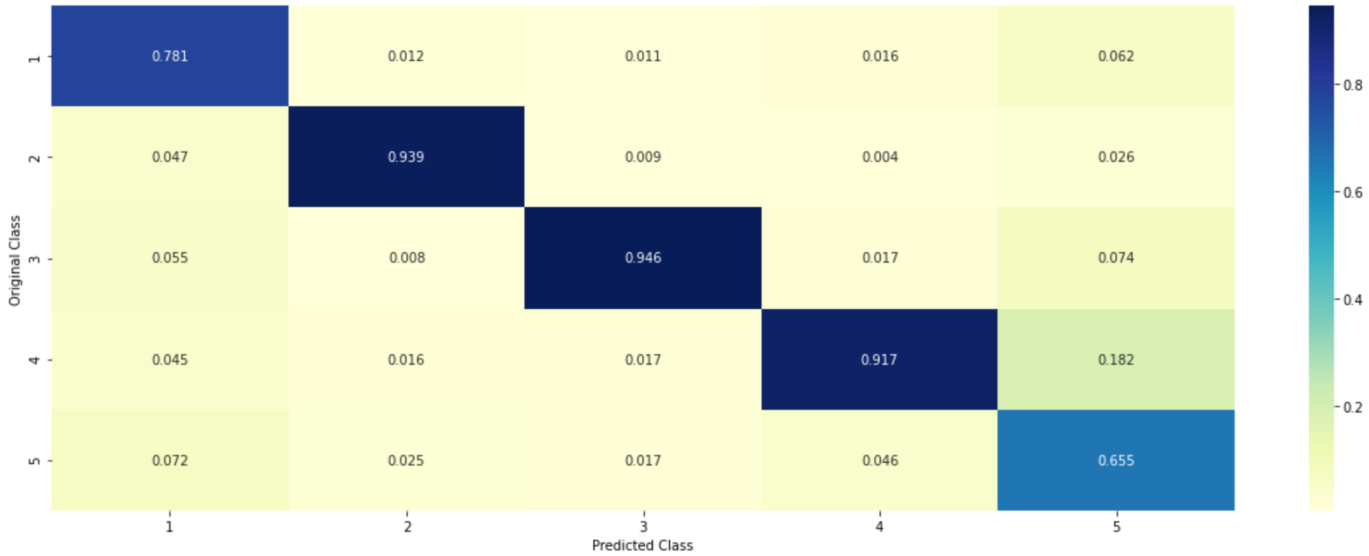
```
Macro F1 score at n=10 is 0.4077635250527141
Macro F1 score at n=20 is 0.4262404492228374
Macro F1 score at n=50 is 0.4225952040360772
Macro F1 score at n=100 is 0.4288806797359914
Macro F1 score at n=150 is 0.4294269621112063
Macro F1 score at n=200 is 0.43443851367103414
Macro F1 score at n=300 is 0.4307376260580201
Macro F1 score at n=500 is 0.4330451401663538
**************************************************
```



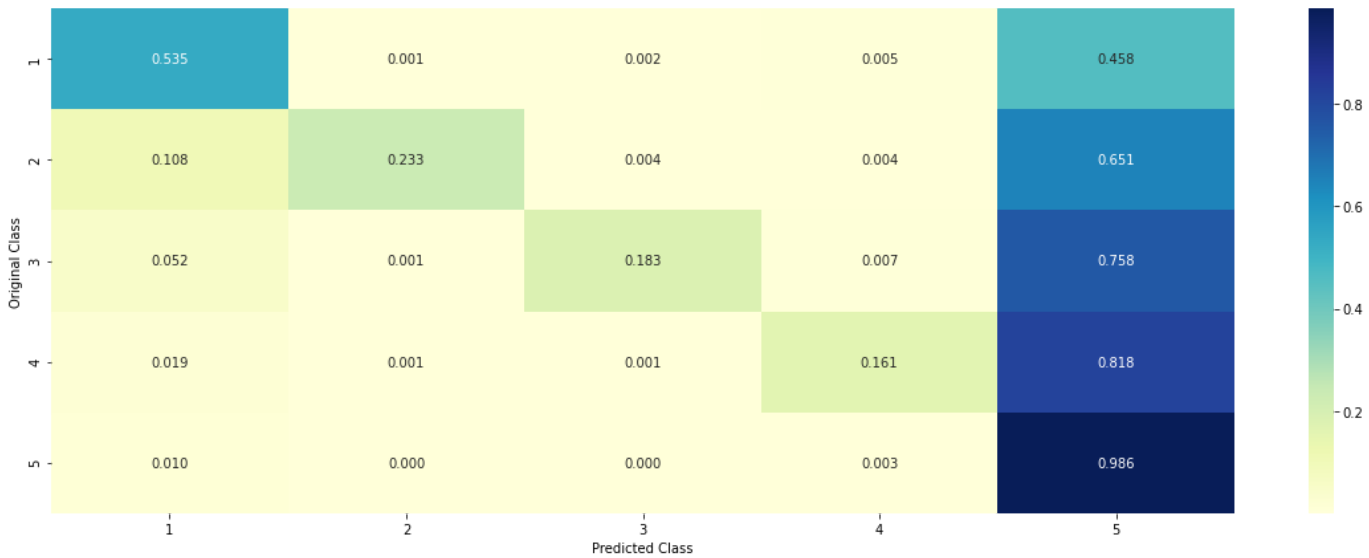

```
**************************************************
Train F1 score at 200 is :0.996856561806245
**************************************************
test F1 score at 200 is :0.47516460218276235
-------------------- Confusion matrix --------------------
```



------------------- Precision matrix (Columm Sum=1) -------------------



------------------- Recall matrix (Row sum=1) -------------------



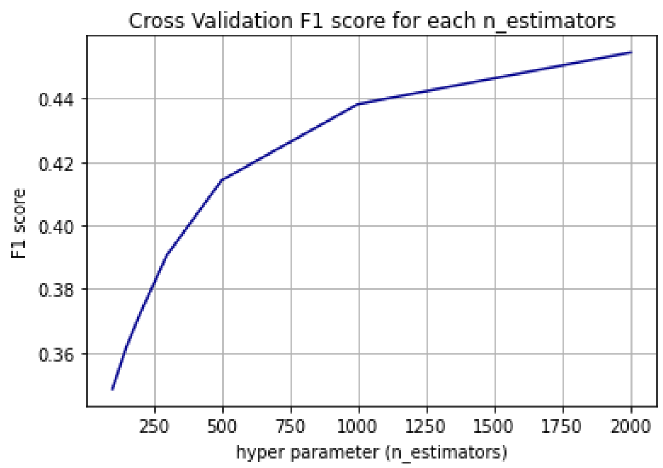
- Model is certainly overfitting.
- Train f1 score is 0.99, whereas test f1 score is 0.43.
- Precision for each class 1,2,3,4 increased compared to previosu models. But recall for 1,2,3,4 are very less.
- Recall for class 5 is 98%, that is model is able to correctly predict 93% of actual class 5 points. For class 1, recall is slightly better 53.5%, Model is able to predict 53.5% of actual class 1 points correctly.
- but for other classes recall is very low. According to business problem we need high recall for class 1,2,3.
- Let us build other models.

1.3.6. LightGBM

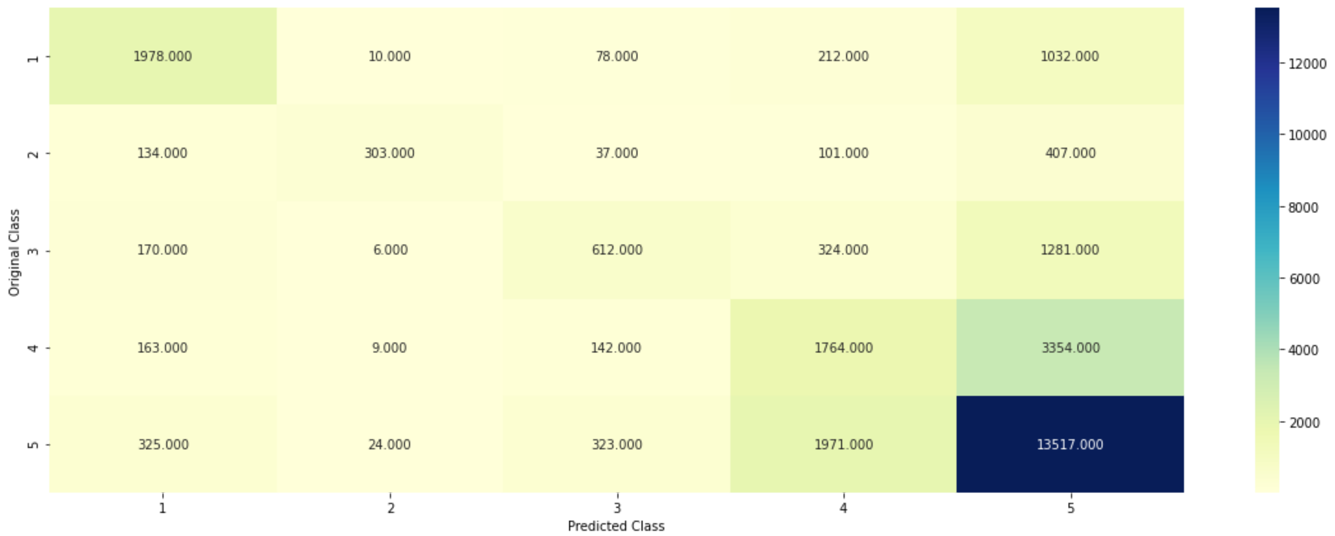
In [41]:
```
import lightgbm as lgb
```

In [42]:
```
n_estimators=[100,150,200,300,500,1000,2000]

f1_scores = []
for i in n_estimators:
    model = None
    model = lgb.LGBMClassifier(n_estimators=i,class_weight="balanced",boosting_type ="goss")
    k_fold_score = kfold(5,model)
    f1_scores.append(k_fold_score)
    print("Macro F1 score at n={} is {} ".format(i,k_fold_score))



print("*"*50)
plt.plot(n_estimators,f1_scores,color="darkblue")

plt.grid()
plt.title("Cross Validation F1 score for each n_estimators")
plt.xlabel("hyper parameter (n_estimators)")
plt.ylabel("F1 score")
plt.show()

best_n = n_estimators[np.argmax(f1_scores)]


model = None
model = lgb.LGBMClassifier(n_estimators=best_n,class_weight='balanced')
model.fit(train,y_train)


print("*"*50)
print("Train F1 score at {} is  :{} ".format(best_n, f1_score(y_train,model.predict(train),labels=model.cl
print("*"*50)
print("test F1 score at {} is :{} ".format(best_n, f1_score(y_test,model.predict(test),labels=model.classe


#plotting confusion matrix

predicted = model.predict(test)
plot_confusion_matrix(y_test,predicted)
```

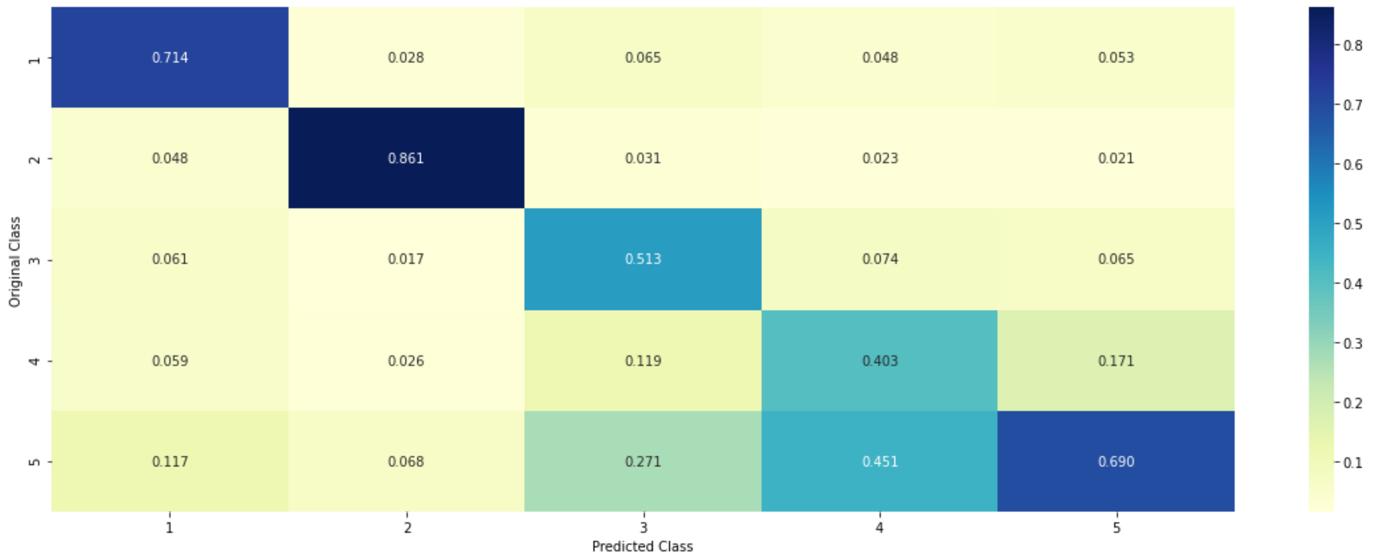
```
Macro F1 score at n=100 is 0.34866288904351816
Macro F1 score at n=150 is 0.3615663865831616
Macro F1 score at n=200 is 0.37206178512386456
Macro F1 score at n=300 is 0.39075914150380475
Macro F1 score at n=500 is 0.4142420051423589
Macro F1 score at n=1000 is 0.4382468652576786
Macro F1 score at n=2000 is 0.45450033475121226
**************************************************
```



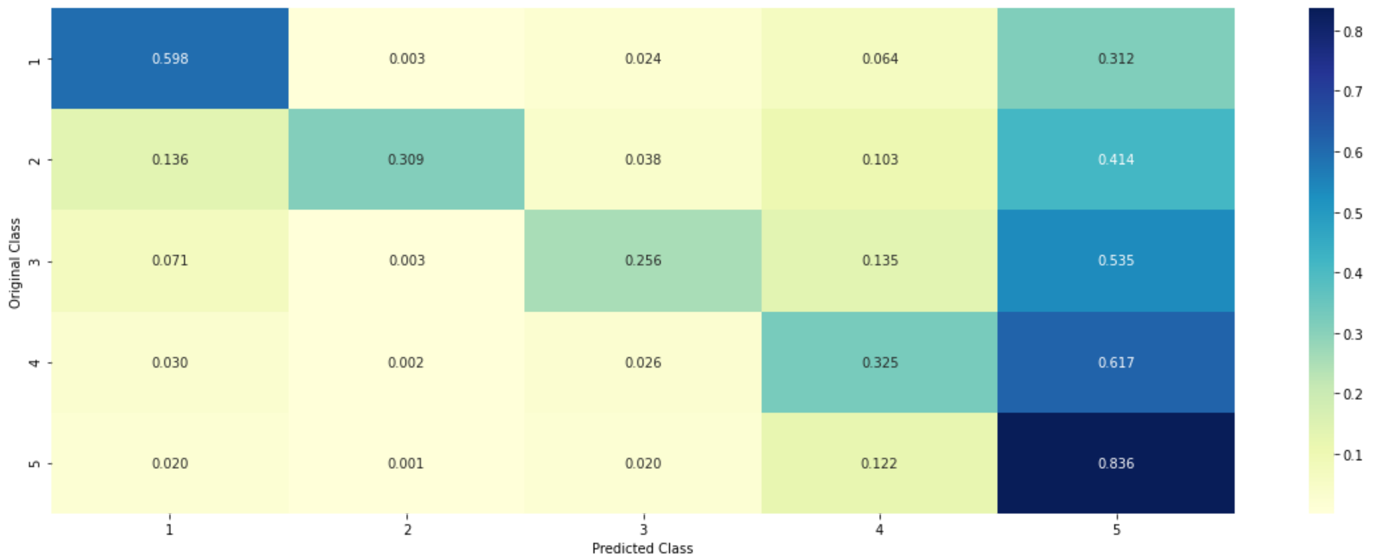

```
**************************************************
Train F1 score at 2000 is  :0.9917689314344624
**************************************************
test F1 score at 2000 is :0.5124762252159244
-------------------- Confusion matrix --------------------
```




```
------------------- Precision matrix (Columm Sum=1) -------------------
```




```
------------------- Recall matrix (Row sum=1) -------------------
```



In [ ]:

```python
print(model.feature_importances_)
```

In [ ]:

We expected better performance from LightGBM model since we have class imbalance. So we used GOSS (Gradient Based One Side Sampling) boosting type in this. As discussed in abstract, this model is better in imbalanced data.

- We can see that model is slightly overfitting. test Macro F1 score is 0.51, which is better than previous models.
- Precision for each class has improved than previous models.
- Recall for class 1,2,3,4 also improved than previous models, which is good.

- Precision for class 4,5 is low, we should imrpove this.
- But as of now, LGBM with goss boosting worked better.
- Recall for class 1 is roughly 60%, for class 2 is 31%, for class 3 25.6%.
- Precision for class 5 is 69%, and for class 4 is 40%.

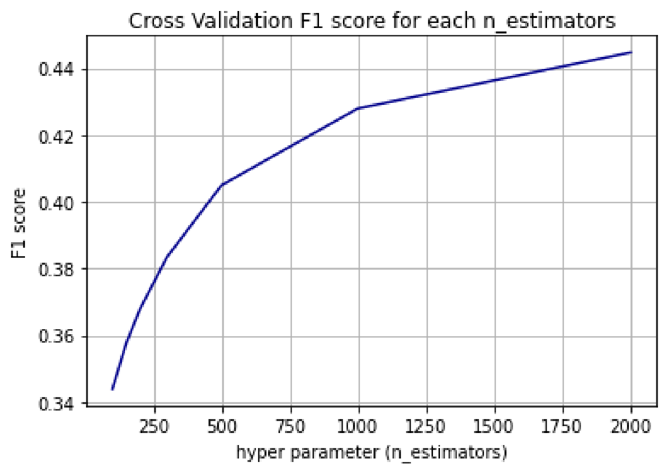
We can see that all models are suffering from overfitting problem.It may due to high dimensionality and useless features. Now let us do feature selection

In [44]:
```
#https://www.analyticsvidhya.com/blog/2020/10/feature-selection-techniques-in-machine-learning/

from sklearn.feature_selection import SelectKBest,f_classif

features = SelectKBest(f_classif,k=60)
train_features = features.fit_transform(train,y_train)
test_features = features.transform(test)
```

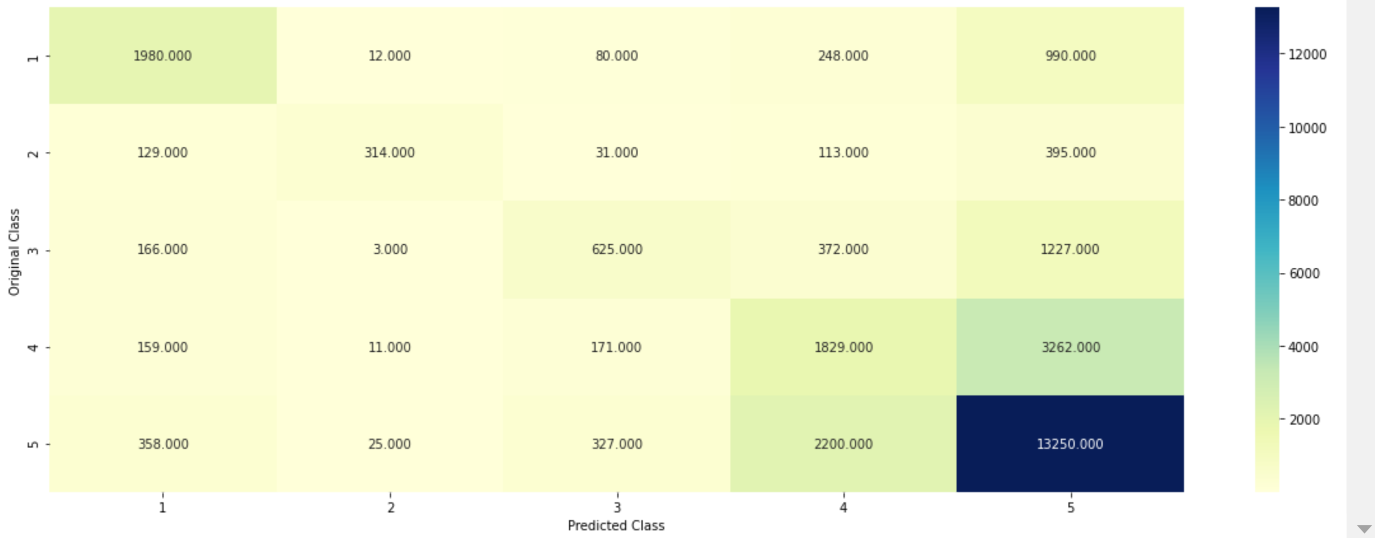
In [ ]:
```
```

In [48]:
```
n_estimators=[100,150,200,300,500,1000,2000]

f1_scores = []
for i in n_estimators:
    model = None
    model = lgb.LGBMClassifier(n_estimators=i,class_weight="balanced",boosting_type ="goss")
    k_fold_score = kfold(5,model,train_features,y_train)
    f1_scores.append(k_fold_score)
    print("Macro F1 score at n={} is {} ".format(i,k_fold_score))



print("*"*50)
plt.plot(n_estimators,f1_scores,color="darkblue")

plt.grid()
plt.title("Cross Validation F1 score for each n_estimators")
plt.xlabel("hyper parameter (n_estimators)")
plt.ylabel("F1 score")
plt.show()

best_n = n_estimators[np.argmax(f1_scores)]


model = None
model = lgb.LGBMClassifier(n_estimators=best_n,class_weight='balanced')
model.fit(train_features,y_train)


print("*"*50)
print("Train F1 score at {} is  :{} ".format(best_n, f1_score(y_train,model.predict(train_features),labels
print("*"*50)
print("test F1 score at {} is :{} ".format(best_n, f1_score(y_test,model.predict(test_features),labels=mod


#plotting confusion matrix

predicted = model.predict(test_features)
plot_confusion_matrix(y_test,predicted)
```

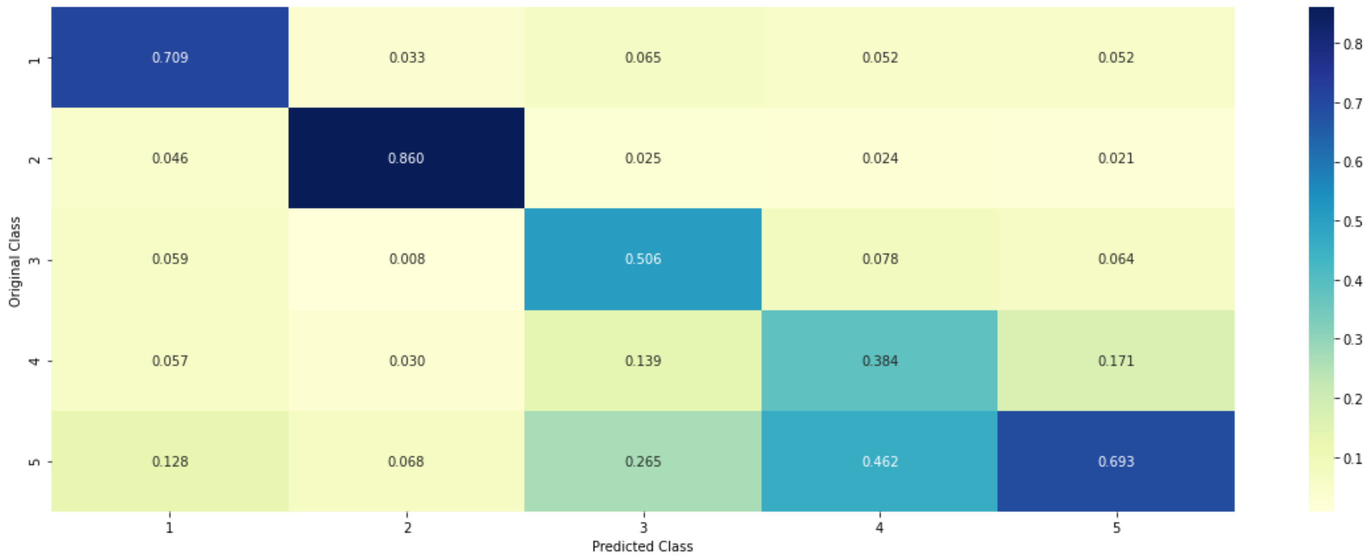
```
Macro F1 score at n=100 is 0.34400786402464406
Macro F1 score at n=150 is 0.35750916676583266
Macro F1 score at n=200 is 0.36769793892850716
Macro F1 score at n=300 is 0.3834348979719837
Macro F1 score at n=500 is 0.4049431141536156
Macro F1 score at n=1000 is 0.42792773804251816
Macro F1 score at n=2000 is 0.44468733953385975
**************************************************
```



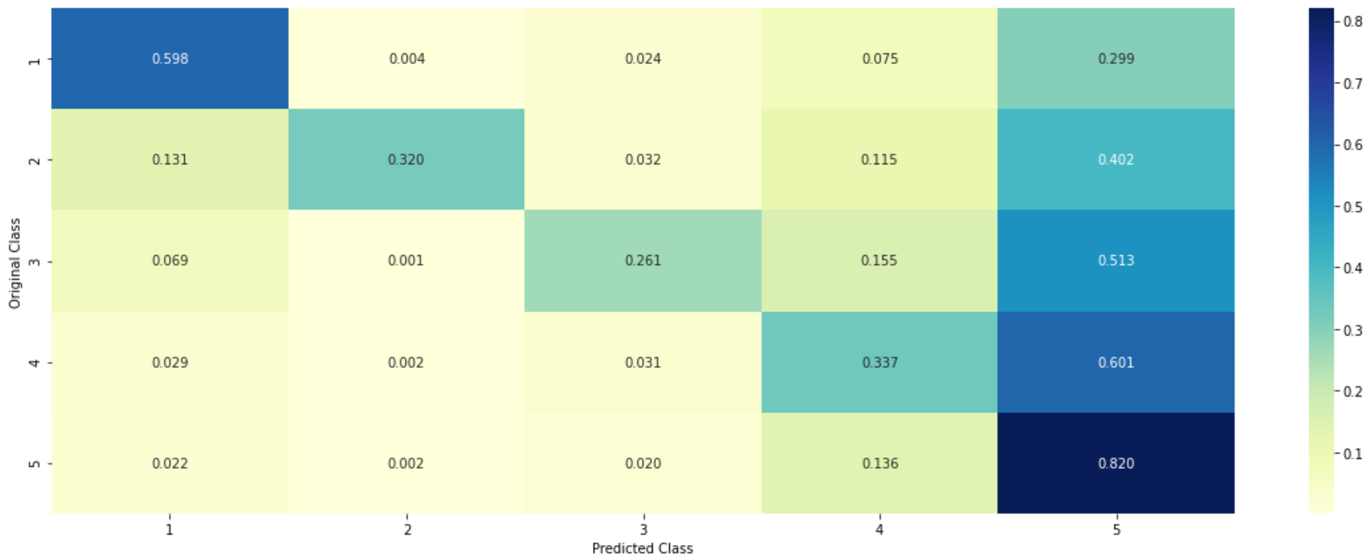

```
**************************************************
Train F1 score at 2000 is  :0.9900946720803109
**************************************************
test F1 score at 2000 is :0.5139426783628179
-------------------- Confusion matrix --------------------
```



------------------- Precision matrix (Columm Sum=1) -------------------



------------------- Recall matrix (Row sum=1) --------------------

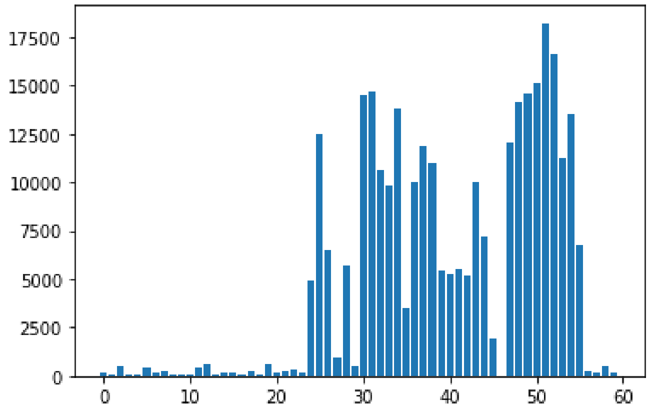


- Not much improvement than previous LGBM model here by selecting top 60 features. Still there is overfitting.
- Recall for class 1 is 60%, class 2 is 32%, class 3 is 26%.
- Precision for class 5 is 69%, class 4 is 38%.

In [49]:
```
importance = model.feature_importances_
```

```
[  185    90   548    62    84   394   128   238    32    78    52   454
   579    91   177   116    42   237   108   565   161   246   314   156
  4928 12506  6513   936  5682   488 14531 14692 10617  9848 13818  3471
  9973 11852 10939  5419  5220  5558  5196 10040  7176  1926     0 12073
 14135 14596 15158 18222 16653 11289 13540  6791   277   168   504   128]
```

In [50]:
```python
importance = model.feature_importances_
plt.bar([x for x in range(len(importance))], importance)
plt.show()
```



In [ ]:
```python

```

LGBM with fine tuning

In [51]:
```python
param_grid = {
    'learning_rate': [0.001, 0.01, 0.1, 0.15,0.2, 0.3],
    'n_estimators': [50,100,200,250,500,1000,2000,2500]}

clf = lgb.LGBMClassifier(n_jobs=-1, class_weight="balanced", boosting_type = "goss")
random_search = RandomizedSearchCV(clf, param_grid, n_iter=30,n_jobs=-1,scoring="f1_macro", verbose=1, cv=
random_search.fit(train, y_train)
```

```
Fitting 5 folds for each of 30 candidates, totalling 150 fits
```

Out[51]:
```
RandomizedSearchCV(cv=5,
                   estimator=LGBMClassifier(boosting_type='goss',
                                            class_weight='balanced'),
                   n_iter=30, n_jobs=-1,
                   param_distributions={'learning_rate': [0.001, 0.01, 0.1,
                                                          0.15, 0.2, 0.3],
                                        'n_estimators': [50, 100, 200, 250, 500,
                                                         1000, 2000, 2500]},
                   random_state=42, refit=False, scoring='f1_macro', verbose=1)
```

In [52]:
```python
params = random_search.best_params_
```

In [53]:
```python
params
```

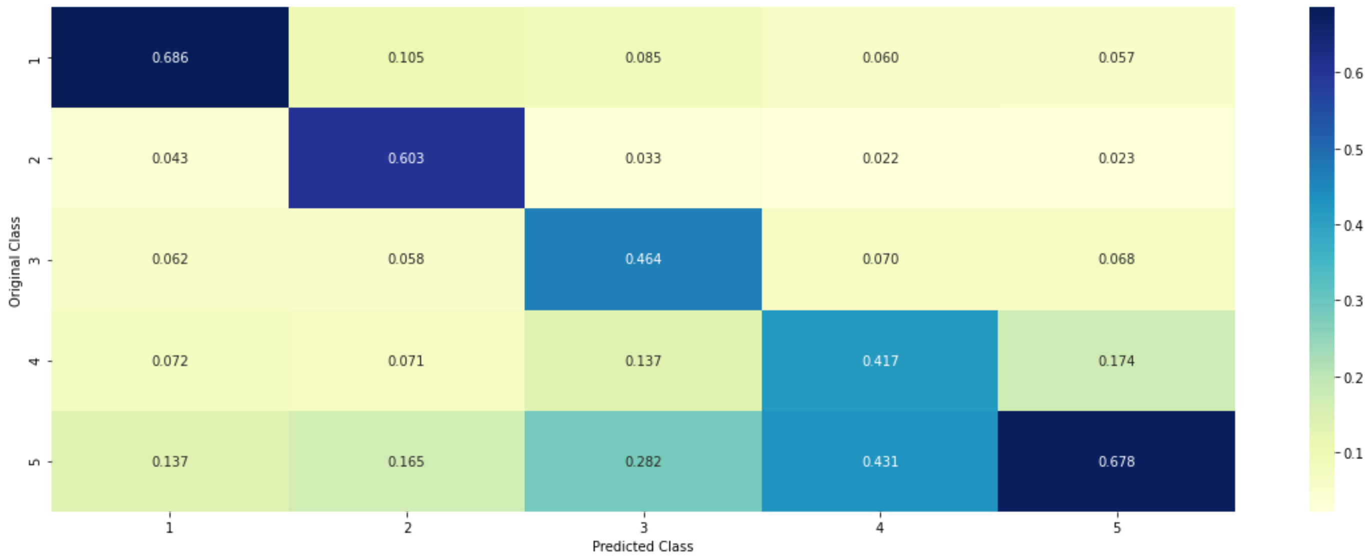
Out[53]:
```
{'n_estimators': 2500, 'learning_rate': 0.15}
```

In [54]:

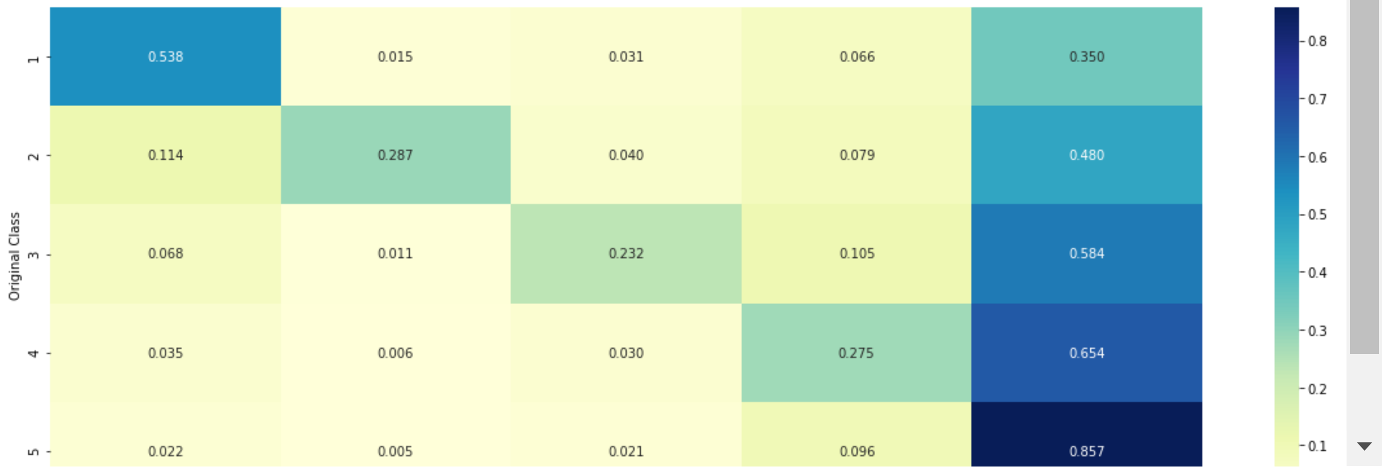
```
clf = lgb.LGBMClassifier(n_estimators= params["n_estimators"],
                          learning_rate= params["learning_rate"], n_jobs=-1,boosting_type = "goss")
clf.fit(train,y_train)

pred_test = clf.predict(test)
pred_train = clf.predict(train)

print("Train F1 score is  :{} ".format(f1_score(y_train,pred_train,labels=[1,2,3,4,5],average="macro")))
print("*"*50)
print("test F1 score is :{} ".format(f1_score(y_test,pred_test,labels=[1,2,3,4,5],average="macro")))

plot_confusion_matrix(y_test,pred_test)
```

```
Train F1 score is  :0.9966341300295701
**************************************************
test F1 score is :0.4780220378617317
-------------------- Confusion matrix --------------------
```


```
-------------------- Precision matrix (Columm Sum=1) --------------------
```




```
-------------------- Recall matrix (Row sum=1) --------------------
```



- No improvemnt got after fine tuning.

In [55]:
```
param_grid = {
    'learning_rate': [0.11,0.13,0.15,0.17,0.19],
    'n_estimators': [2000,2500]}

clf = lgb.LGBMClassifier(n_jobs=-1, class_weight="balanced", boosting_type = "goss")
random_search = RandomizedSearchCV(clf, param_grid, n_iter=30,n_jobs=-1,scoring="f1_macro", verbose=1, cv=
random_search.fit(train, y_train)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
```

Out[55]:
```
RandomizedSearchCV(cv=5,
                   estimator=LGBMClassifier(boosting_type='goss',
                                            class_weight='balanced'),
                   n_iter=30, n_jobs=-1,
                   param_distributions={'learning_rate': [0.11, 0.13, 0.15,
                                                          0.17, 0.19],
                                        'n_estimators': [2000, 2500]},
                   random_state=42, refit=False, scoring='f1_macro', verbose=1)
```

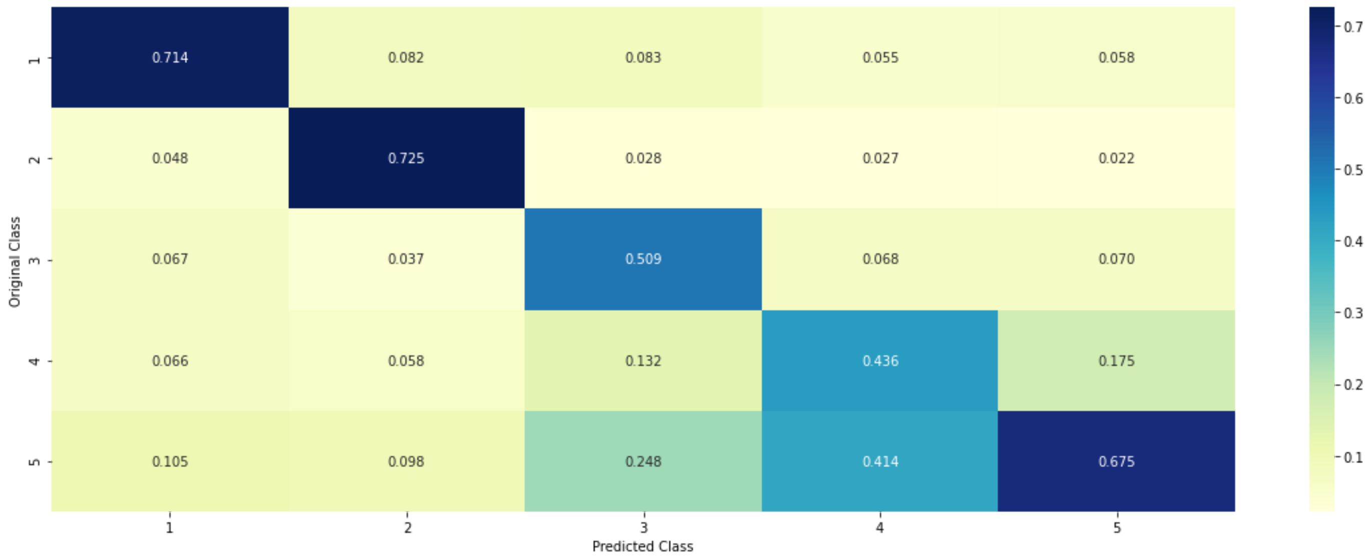
In [56]:
```
params = random_search.best_params_
print(params)
```

```
{'n_estimators': 2500, 'learning_rate': 0.11}
```

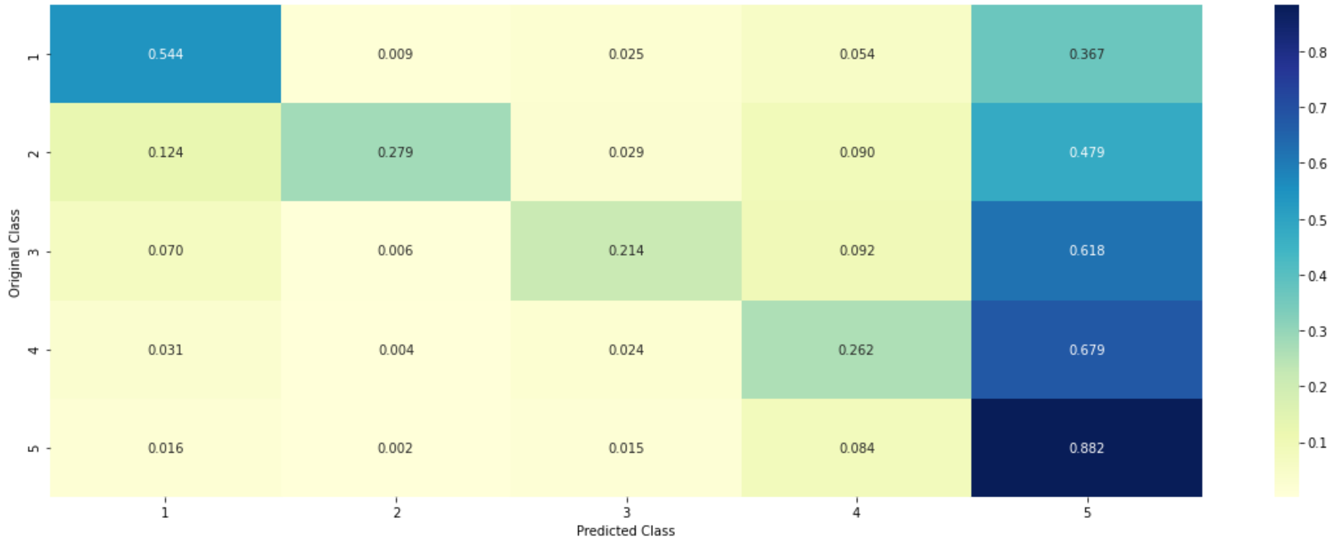
In [57]:
```
clf = lgb.LGBMClassifier(n_estimators= params["n_estimators"],
                        learning_rate= params["learning_rate"], n_jobs=-1,boosting_type = "goss")
clf.fit(train,y_train)

pred_test = clf.predict(test)
pred_train = clf.predict(train)

print("Train F1 score is  :{} ".format(f1_score(y_train,pred_train,labels=[1,2,3,4,5],average="macro")))
print("*"*50)
print("test F1 score is :{} ".format(f1_score(y_test,pred_test,labels=[1,2,3,4,5],average="macro")))

plot_confusion_matrix(y_test,pred_test)
```

```
Train F1 score is  :0.9948076389453145
**************************************************
test F1 score is :0.48265996903374164
-------------------- Confusion matrix --------------------
```


```
-------------------- Precision matrix (Columm Sum=1) --------------------
```




```
-------------------- Recall matrix (Row sum=1) --------------------
```



- No improvement by fine tuning.

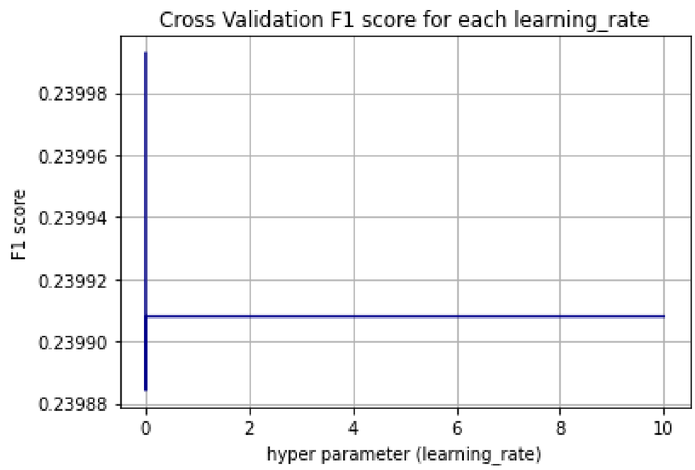
1.3.7. XGBoost

In [35]:
```
learning_rate=[0.00001,0.0001,0.001,0.01,0.1,1,10]

f1_scores = []
for i in learning_rate:
    model = None
    model = xgb.XGBClassifier(learning_rate=i)
    k_fold_score = kfold(5,model)
    f1_scores.append(k_fold_score)
    print("Macro F1 score at learning_rate={} is {} ".format(i,k_fold_score))



print("*"*50)
plt.plot(learning_rate,f1_scores,color="darkblue")

plt.grid()
plt.title("Cross Validation F1 score for each learning_rate")
plt.xlabel("hyper parameter (learning_rate)")
plt.ylabel("F1 score")
plt.show()

best_n = learning_rate[np.argmax(f1_scores)]


model = None
model = xgb.XGBClassifier(learning_rate=best_n,class_weight='balanced')
model.fit(train,y_train)


print("*"*50)
print("Train F1 score at {} is  :{} ".format(best_n, f1_score(y_train,model.predict(train),labels=model.cl
print("*"*50)
print("test F1 score at {} is :{} ".format(best_n, f1_score(y_test,model.predict(test),labels=model.classe


#plotting confusion matrix

predicted = model.predict(test)
plot_confusion_matrix(y_test,predicted)
```

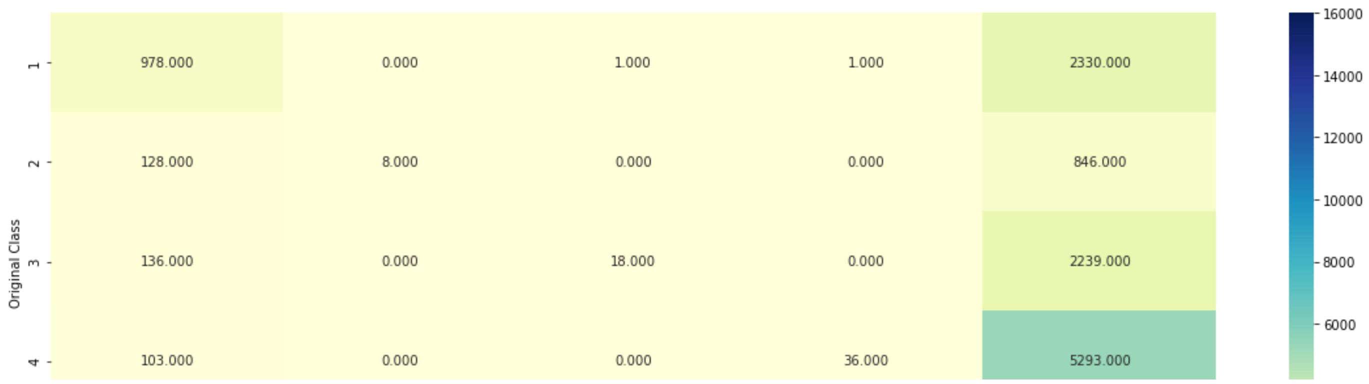
```
[08:42:38] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[08:43:20] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[08:44:03] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[08:44:46] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[08:45:31] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
Macro F1 score at learning_rate=1e-05 is 0.23999286624756397
[08:46:15] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[08:46:59] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[08:47:43] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[08:48:27] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
```

```
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[08:49:12] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
Macro F1 score at learning_rate=0.0001 is 0.2399129365344345
[08:49:55] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[08:50:39] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[08:51:24] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[08:52:07] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[08:52:52] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
Macro F1 score at learning_rate=0.001 is 0.23988413030748137
[08:53:36] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[08:54:21] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[08:55:05] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[08:55:50] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[08:56:34] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
Macro F1 score at learning_rate=0.01 is 0.23990800796359396
[08:57:19] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[08:58:03] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[08:58:48] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[08:59:32] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[09:00:15] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
Macro F1 score at learning_rate=0.1 is 0.23990800796359396
[09:00:58] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.

[09:01:42] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
```

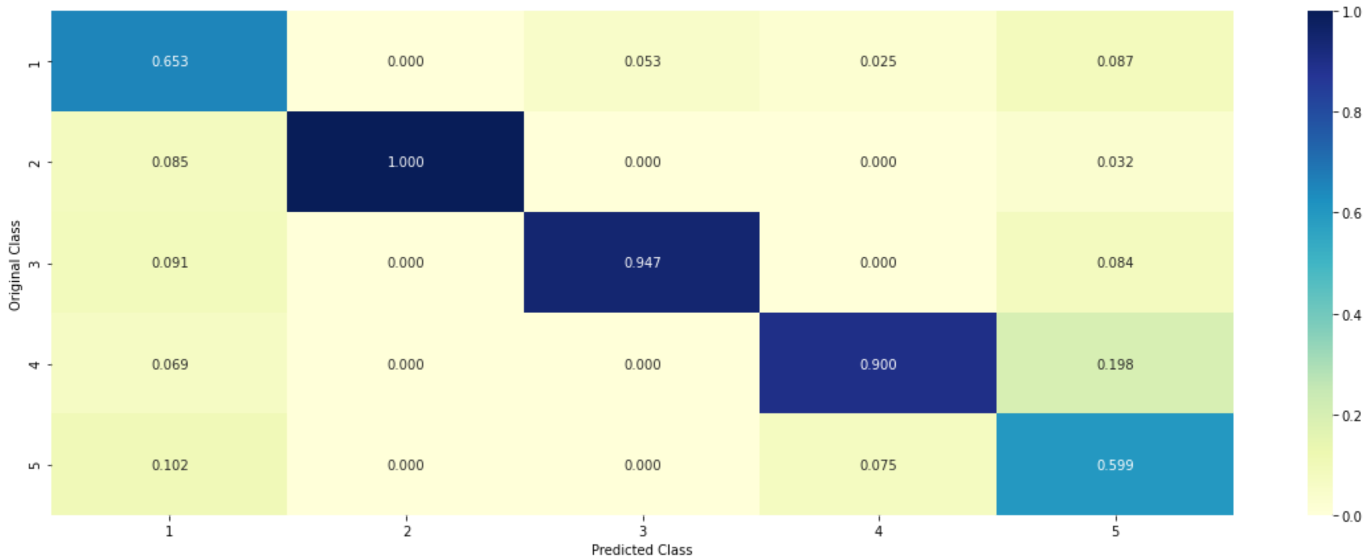
```
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[09:02:26] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[09:03:10] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[09:03:54] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
Macro F1 score at learning_rate=1 is 0.23990800796359396
[09:04:38] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[09:05:23] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[09:06:12] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[09:06:58] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[09:07:43] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
Macro F1 score at learning_rate=10 is 0.23990800796359396
**************************************************
```



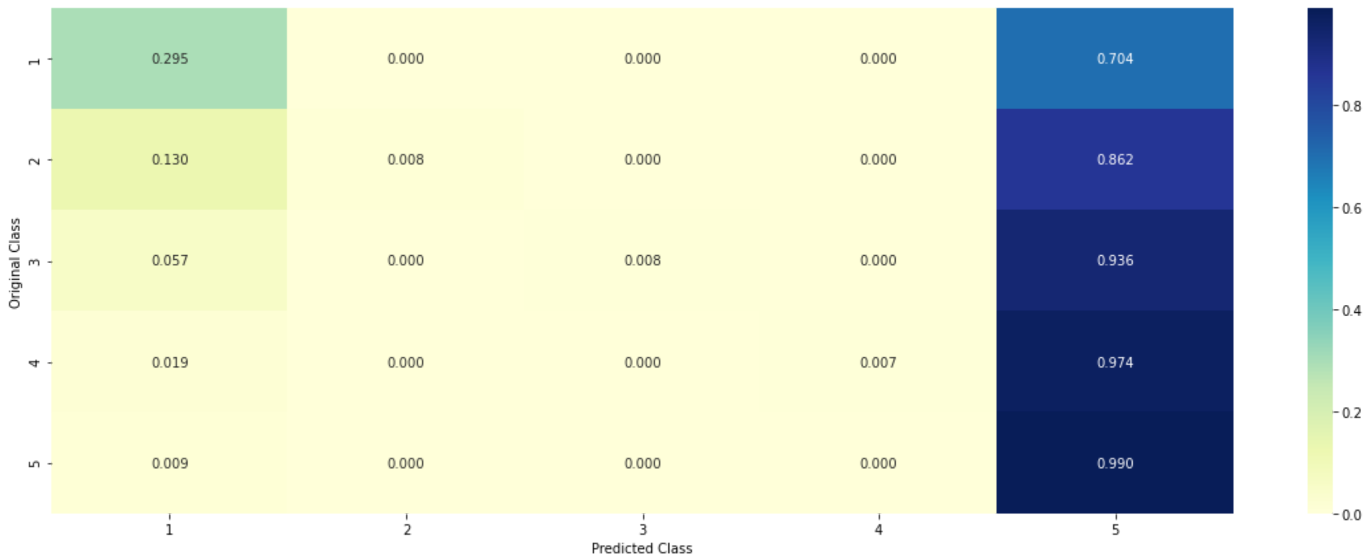

```
[09:07:44] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:541:
Parameters: { class_weight } might not be used.

  This may not be accurate due to some parameters are only used in language bindings but
  passed down to XGBoost core.  Or some parameters are not used but slip through this
  verification. Please open an issue if you find above cases.


[09:08:40] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: St
arting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was chan
ged from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
**************************************************
Train F1 score at 1e-05 is  :0.24882217413212637
**************************************************
test F1 score at 1e-05 is :0.23953227226579532
-------------------- Confusion matrix --------------------
```




```
------------------- Precision matrix (Columm Sum=1) -------------------
```




```
------------------- Recall matrix (Row sum=1) --------------------
```



- XGBRFClassifier is not working good. Recall for class 2,3,4 are very less. but precision is high for this class.
- And recall for class 5 is high, But precision is just 59%.
- It seems that it is not giving importance to class 2,3,4.

XGBoost with fine hyperparameter tuning

In [36]:
```
param_grid = {
    'max_depth': [2,3,4,5,6,7,8],
    'learning_rate': [0.001, 0.01, 0.1, 0.2, 0.3],
    'n_estimators': [5,10,50,100,200,250]}

clf = xgb.XGBClassifier(n_jobs=-1 ,early_stopping_rounds = 10, eta = 0.02 )
random_search = RandomizedSearchCV(clf, param_grid, n_iter=30,n_jobs=-1,scoring="f1_macro", verbose=1, cv=
random_search.fit(train, y_train)
```

```
Fitting 5 folds for each of 30 candidates, totalling 150 fits
```

Out[36]:
```
RandomizedSearchCV(cv=5,
                   estimator=XGBClassifier(base_score=None, booster=None,
                                           colsample_bylevel=None,
                                           colsample_bynode=None,
                                           colsample_bytree=None,
                                           early_stopping_rounds=10, eta=0.02,
                                           gamma=None, gpu_id=None,
                                           importance_type='gain',
                                           interaction_constraints=None,
                                           learning_rate=None,
                                           max_delta_step=None, max_depth=None,
                                           min_child_weight=None, missing=nan,
                                           monotone_...
                                           num_parallel_tree=None,
                                           random_state=None, reg_alpha=None,
                                           reg_lambda=None,
                                           scale_pos_weight=None,
                                           subsample=None, tree_method=None,
                                           validate_parameters=None,
                                           verbosity=None),
                   n_iter=30, n_jobs=-1,
                   param_distributions={'learning_rate': [0.001, 0.01, 0.1, 0.2,
                                                          0, 3],
                                        'max_depth': [2, 3, 4, 5, 6, 7, 8],
                                        'n_estimators': [5, 10, 50, 100, 200,
                                                         250]},
                   random_state=42, refit=False, scoring='f1_macro', verbose=1)
```

In [ ]:
```
```

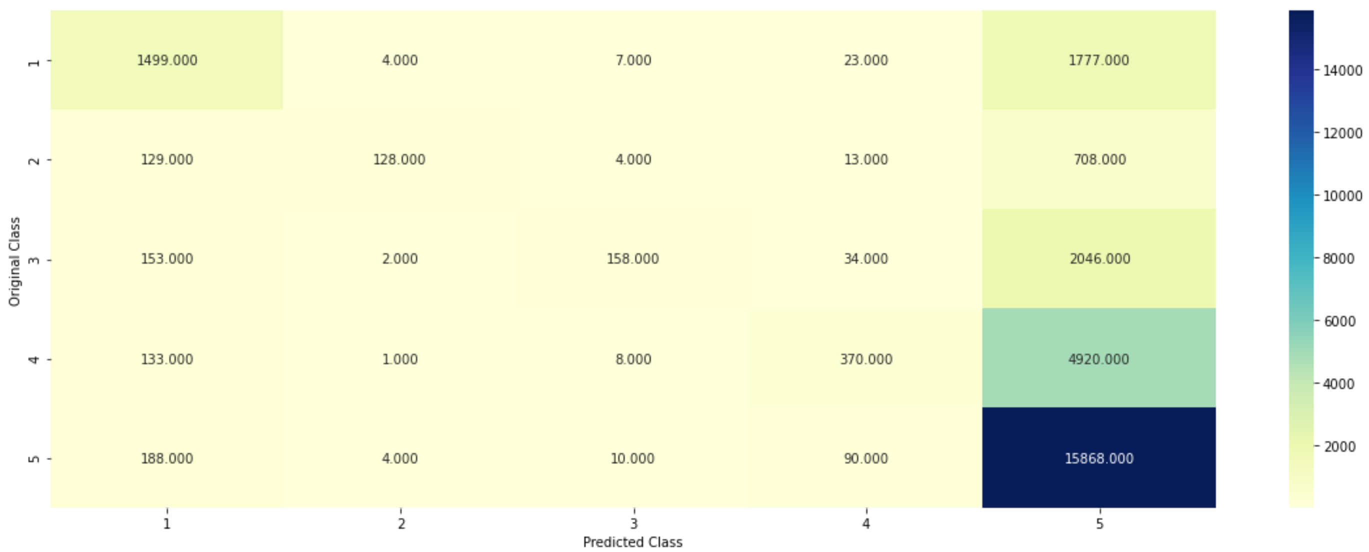
In [37]:
```
params = random_search.best_params_
```

In [38]:
```
params
```

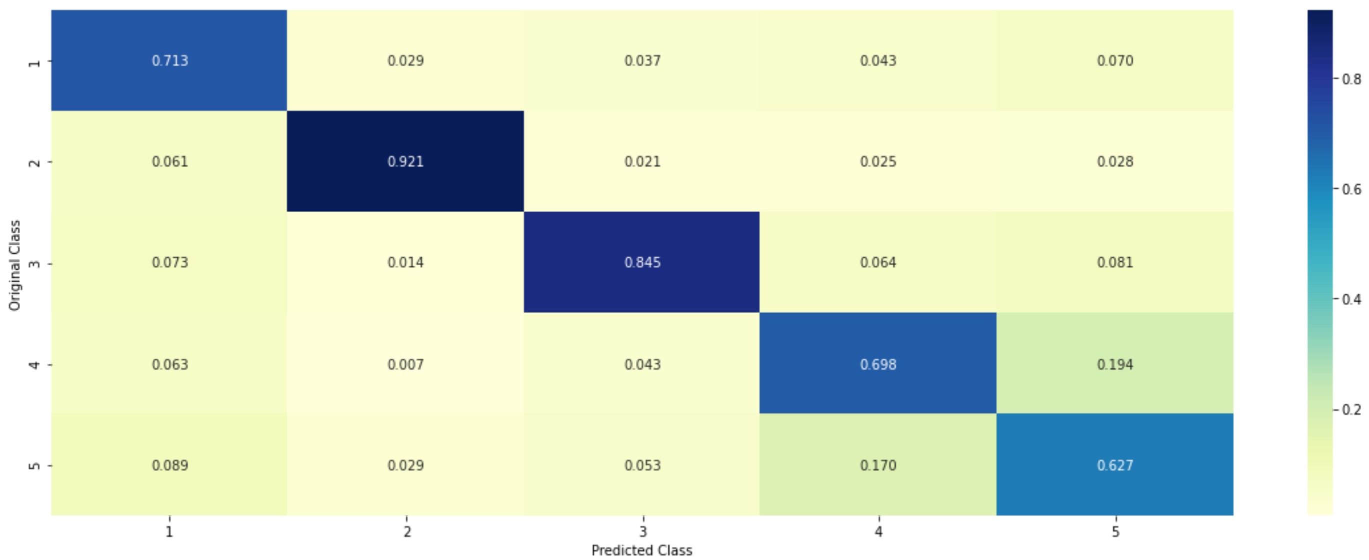
Out[38]:
```
{'n_estimators': 100, 'max_depth': 8, 'learning_rate': 0.2}
```

In [39]:
```python
clf = xgb.XGBClassifier(n_estimators= params["n_estimators"], max_depth= params["max_depth"],
                        learning_rate= params["learning_rate"]  ,early_stopping_rounds = 10, eta = 0.02 )

clf.fit(train,y_train)

pred_test = clf.predict(test)
pred_train = clf.predict(train)

print("Train F1 score is  :{} ".format(f1_score(y_train,pred_train,labels=[1,2,3,4,5],average="macro")))
print("*"*50)
print("test F1 score is :{} ".format(f1_score(y_test,pred_test,labels=[1,2,3,4,5],average="macro")))

plot_confusion_matrix(y_test,pred_test)
```

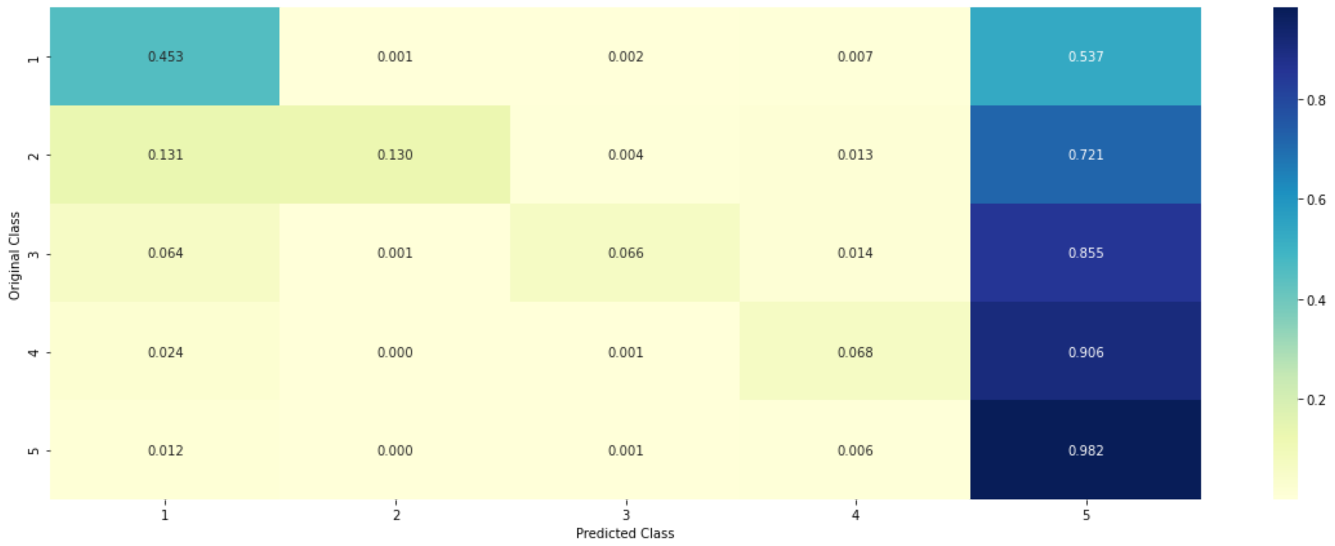
```
[10:31:44] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:541:
Parameters: { early_stopping_rounds } might not be used.

  This may not be accurate due to some parameters are only used in language bindings but
  passed down to XGBoost core.  Or some parameters are not used but slip through this
  verification. Please open an issue if you find above cases.


[10:31:46] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: St
arting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was chan
ged from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
Train F1 score is  :0.5387918992086534
**************************************************
test F1 score is :0.35880636075112976
-------------------- Confusion matrix --------------------
```




```
-------------------- Precision matrix (Columm Sum=1) --------------------
```




```
-------------------- Recall matrix (Row sum=1) --------------------
```



- This works slightly better for class 5 and class 1. But class 2,3,4 are suffuring from misclassification as before. Recall for class 2,3,4 are very less.
- Macro f1 score is also not much good.

Macro F1 score is not improving much. Also there is misclassification, this may due to class imbalance. So we need class balancing techniques.

Let us try Random Over Sampling technique to handle class imbalance.

1.4 Random Over Sampling

In [58]:
```
from imblearn.over_sampling import RandomOverSampler
from imblearn.under_sampling import RandomUnderSampler
```

In [59]:
```
om = RandomOverSampler(random_state=10)
x_res , y_res = om.fit_resample(train_features,y_train)
```

In [60]:
```
x_res.shape
```

Out[60]:
```
(242385, 60)
```

In [61]:
```
print("class distribution BEFORE SMOTE in train data: \n",y_train.value_counts())
print("class distribution AFTER SMOTE in train data: \n",y_res.value_counts())
```

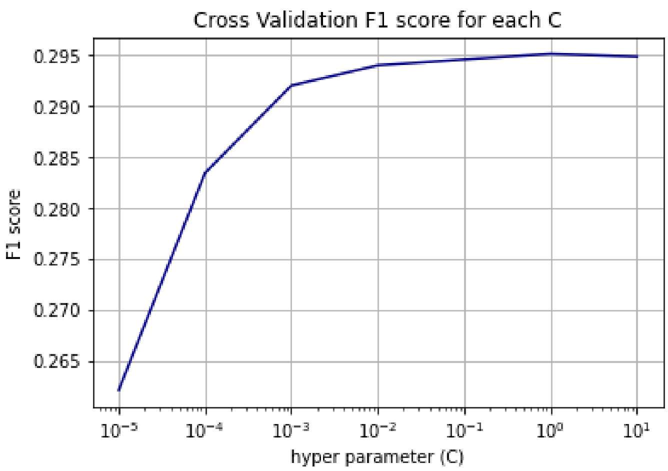
```
class distribution BEFORE SMOTE in train data:
 5    48477
4    16293
1     9931
3     7180
2     2947
Name: review_score, dtype: int64
class distribution AFTER SMOTE in train data:
 4    48477
3    48477
5    48477
2    48477
1    48477
Name: review_score, dtype: int64
```

In [66]:
```
def kfold_sampling(k,model):
    """This function will do stratified k-fold cross_validation"""
    kf = StratifiedKFold(n_splits=k)

    cv_f1_score = []
    for tr_ind,cv_ind in kf.split(x_res,y_res):

        x_tr,x_cv,y_tr,y_cv = x_res[tr_ind],x_res[cv_ind],y_res[tr_ind],y_res[cv_ind]

        model.fit(x_tr,y_tr)
        pred_cv = model.predict(x_cv)
        cv_f1_score.append((f1_score(y_cv,pred_cv,average="macro",labels=[1,2,3,4,5])))

    return np.mean(cv_f1_score)
```

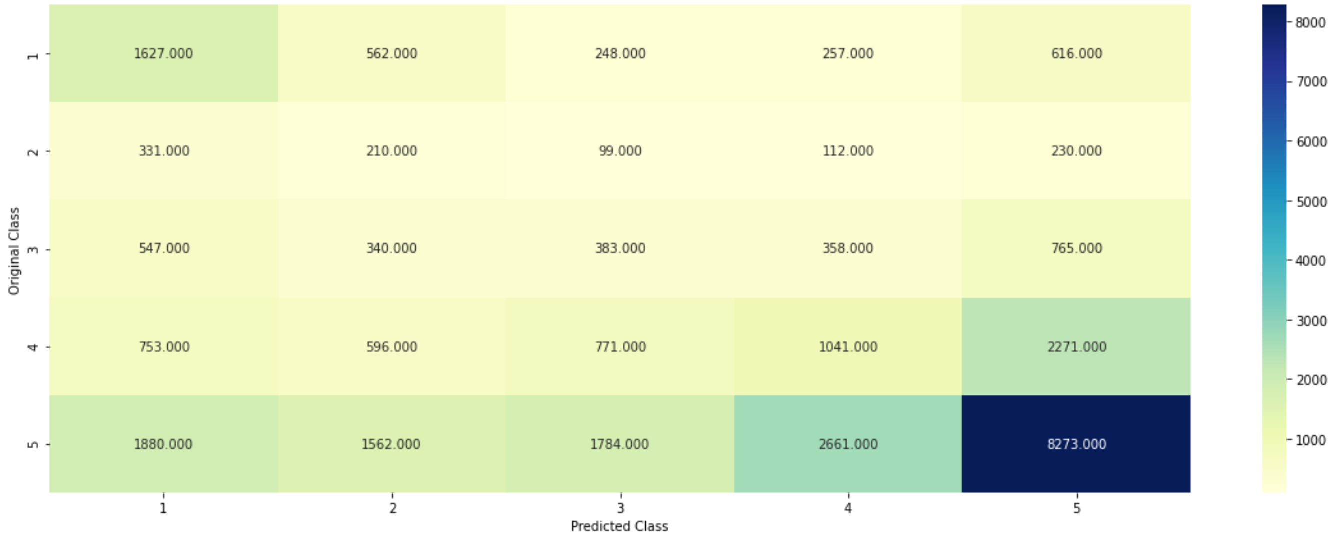
1.4.1 Logistic Regression:

In [64]:
```
C=[0.00001,0.0001,0.001,0.01,0.1,1,10]

f1_scores = []
for i in C:
    model = None
    model = LogisticRegression(C=i)
    k_fold_score = kfold_sampling(5,model)
    f1_scores.append(k_fold_score)
    print("Macro F1 score at C={} is {} ".format(i,k_fold_score))



print("*"*50)
plt.plot(C,f1_scores,color="darkblue")
plt.xscale("log")
plt.grid()
plt.title("Cross Validation F1 score for each C")
plt.xlabel("hyper parameter (C)")
plt.ylabel("F1 score")
plt.show()

best_param = C[np.argmax(f1_scores)]

model = None
model = LogisticRegression(C=i)
model.fit(x_res,y_res)


print("*"*50)
print("Train F1 score at {} is :{}".format(best_param, f1_score(y_res,model.predict(x_res),labels=model.cl
print("*"*50)
print("test F1 score at {} is :{}".format(best_param, f1_score(y_test,model.predict(test_features),labels=


#plotting confusion matrix
predicted = model.predict(test_features)
plot_confusion_matrix(y_test,predicted)
```

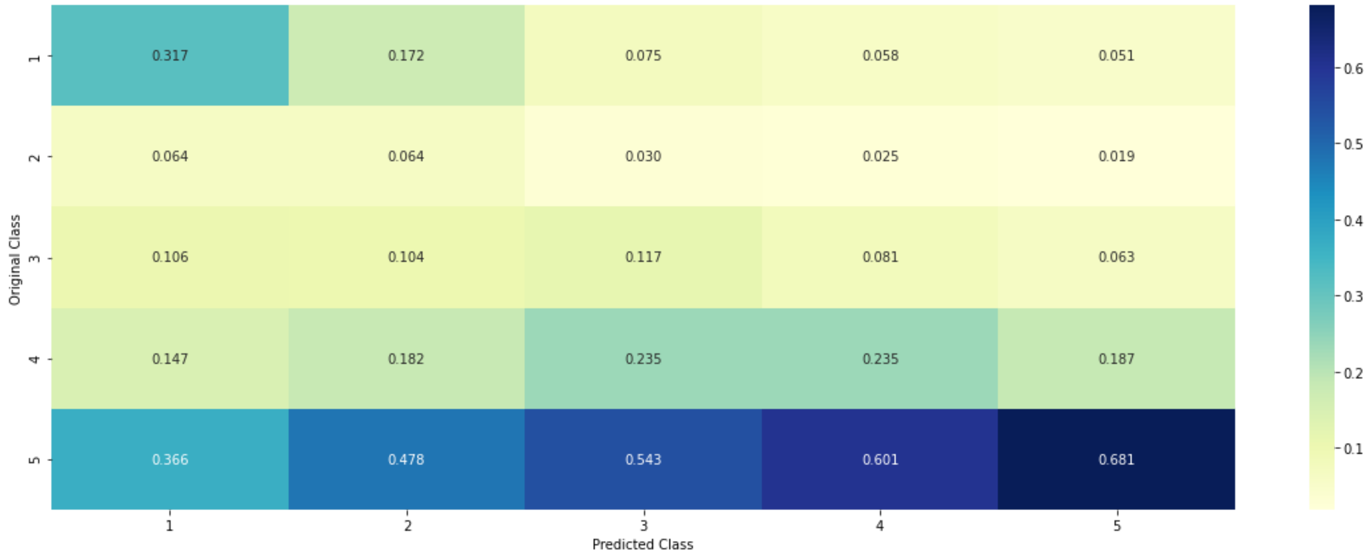
```
Macro F1 score at C=1e-05 is 0.2620845225477523
Macro F1 score at C=0.0001 is 0.2833944832922826
Macro F1 score at C=0.001 is 0.2919762997087313
Macro F1 score at C=0.01 is 0.29396414803265347
Macro F1 score at C=0.1 is 0.29453436831243
Macro F1 score at C=1 is 0.29510303180450576
Macro F1 score at C=10 is 0.29481818351258066
**************************************************
```



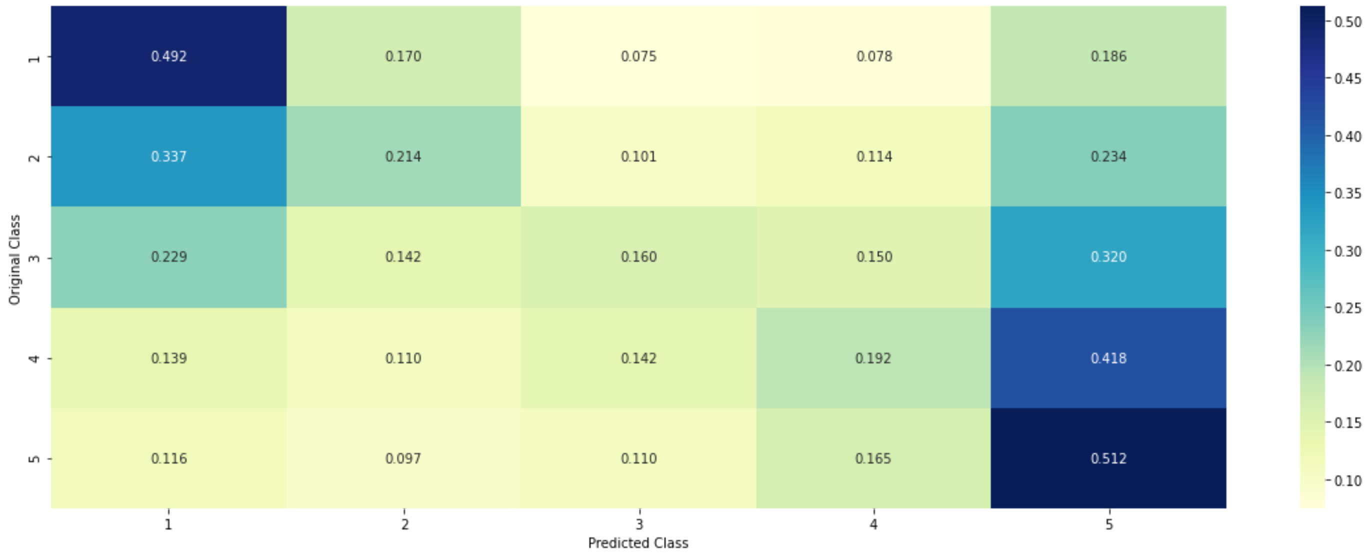

```
**************************************************
Train F1 score at 1 is :0.29554956053539866
**************************************************
test F1 score at 1 is :0.28287059666769154
-------------------- Confusion matrix --------------------
```




```
-------------------- Precision matrix (Columm Sum=1) --------------------
```




```
-------------------- Recall matrix (Row sum=1) --------------------
```



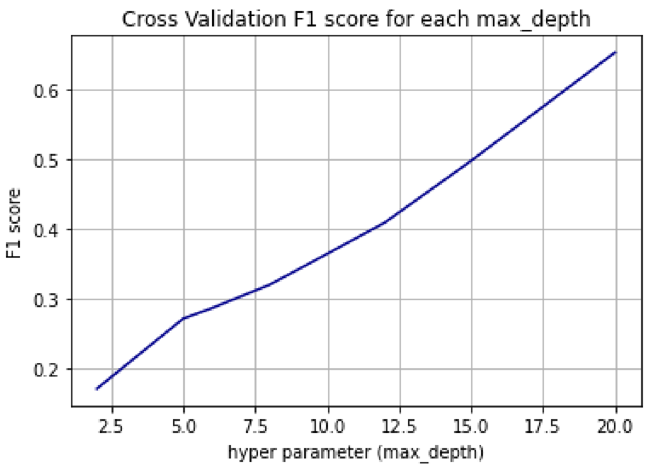
In [ ]:

In [ ]:

1.4.2. Decision Tree

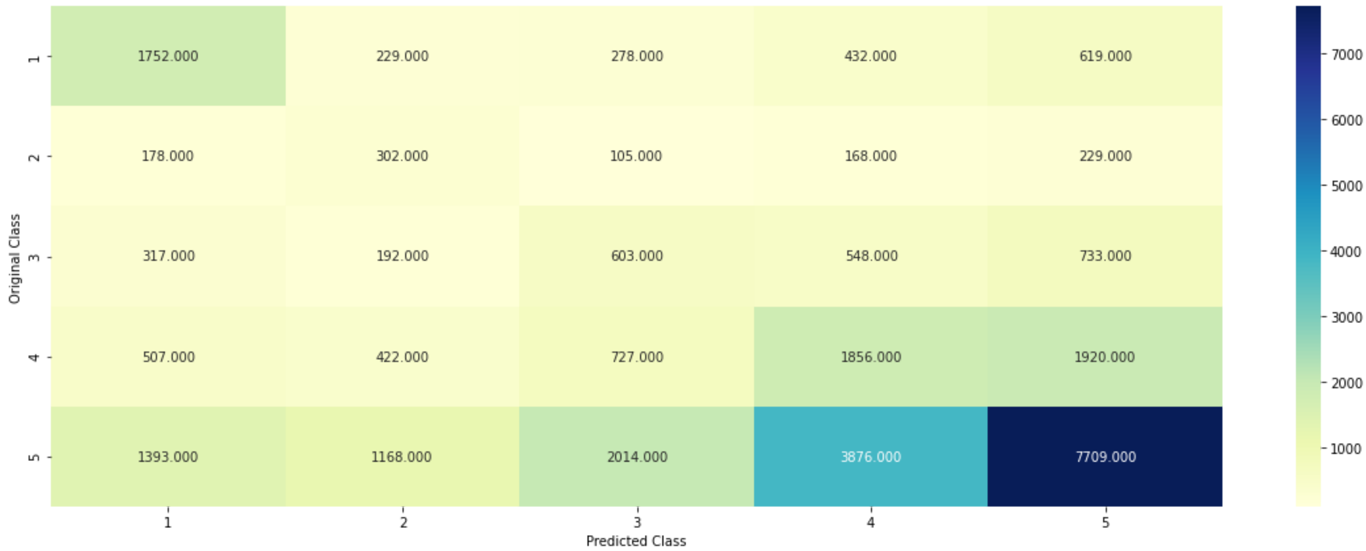
In [69]:
```
max_depth=[2,5,6,8,10,12,15,20]

f1_scores = []
for i in max_depth:
    model = None
    model = DecisionTreeClassifier(max_depth=i)
    k_fold_score = kfold_sampling(5,model)
    f1_scores.append(k_fold_score)
    print("Macro F1 score at n={} is {} ".format(i,k_fold_score))



print("*"*50)
plt.plot(max_depth,f1_scores,color="darkblue")

plt.grid()
plt.title("Cross Validation F1 score for each max_depth")
plt.xlabel("hyper parameter (max_depth)")
plt.ylabel("F1 score")
plt.show()

best_param = max_depth[np.argmax(f1_scores)]

model = None
model = DecisionTreeClassifier(max_depth=best_param)
model.fit(x_res,y_res)


print("*"*50)
print("Train F1 score at {} is :{}".format(best_param, f1_score(y_res,model.predict(x_res),labels=model.cl
print("*"*50)
print("test F1 score at {} is :{}".format(best_param, f1_score(y_test,model.predict(test_features),labels=


#plotting confusion matrix
predicted = model.predict(test_features)
plot_confusion_matrix(y_test,predicted)
```

```
Macro F1 score at n=2 is 0.17082335139712285
Macro F1 score at n=5 is 0.2713285349133917
Macro F1 score at n=6 is 0.2863762832795523
Macro F1 score at n=8 is 0.3197392847300593
Macro F1 score at n=10 is 0.3641308575548703
Macro F1 score at n=12 is 0.40877818290076495
Macro F1 score at n=15 is 0.49739722106370027
Macro F1 score at n=20 is 0.6526854356549808
**************************************************
```

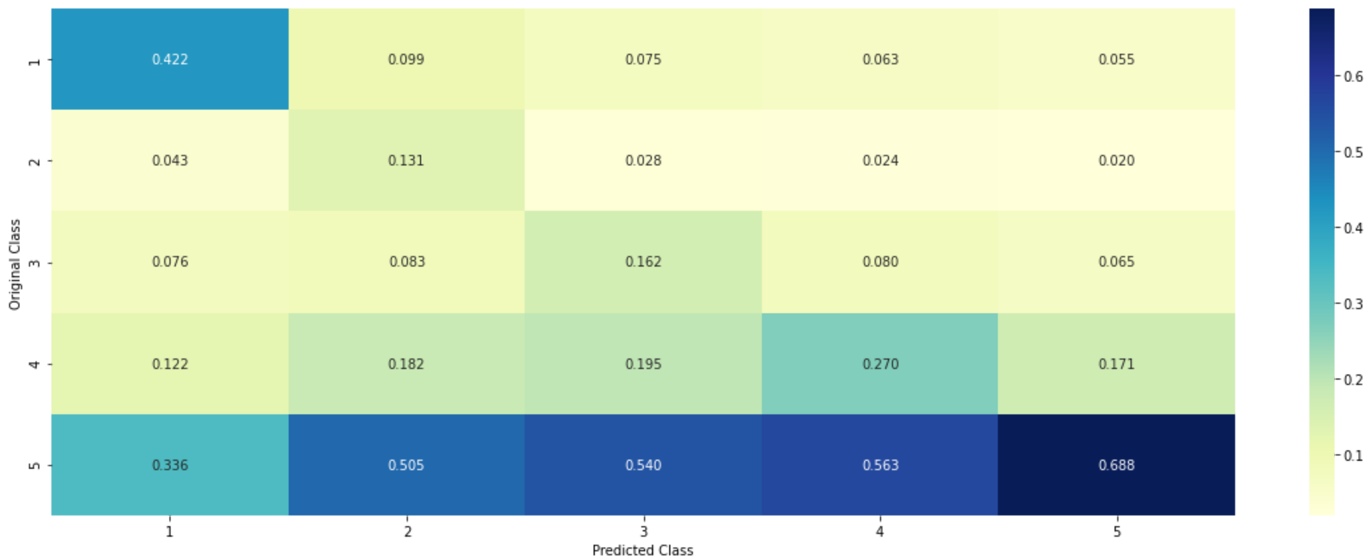



```
**************************************************
Train F1 score at 20 is :0.7016532041986847
**************************************************
```

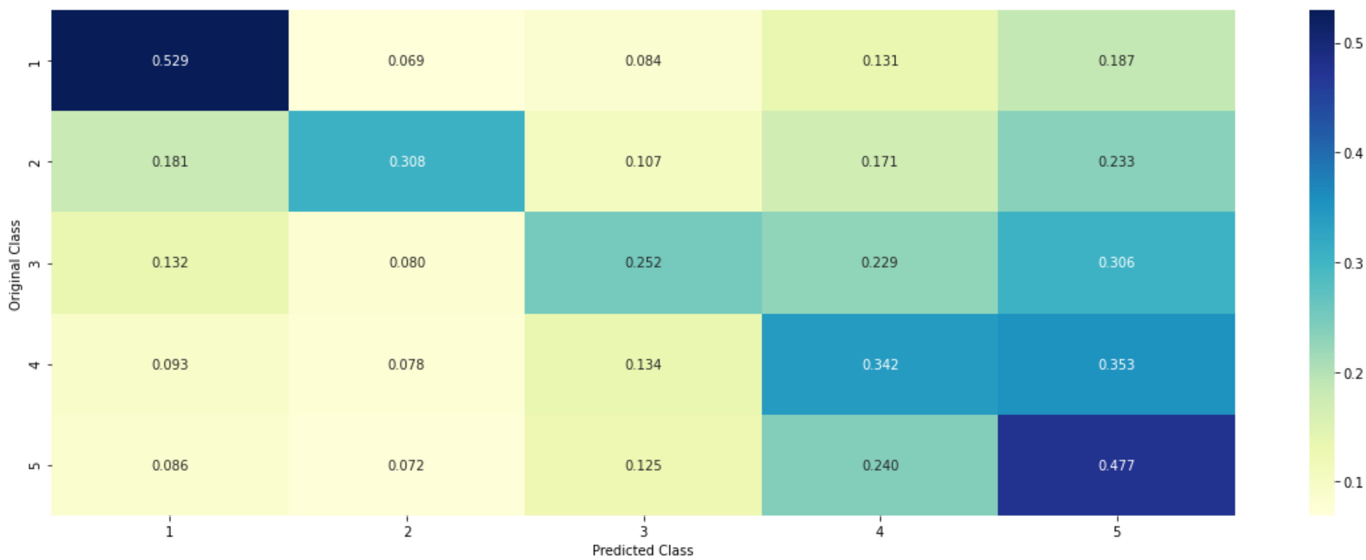
```
test F1 score at 20 is :0.34301458062753587
-------------------- Confusion matrix --------------------
```




```
-------------------- Precision matrix (Columm Sum=1) --------------------
```




```
-------------------- Recall matrix (Row sum=1) --------------------
```



- And no much good performance on any class label.
- High misclassification.

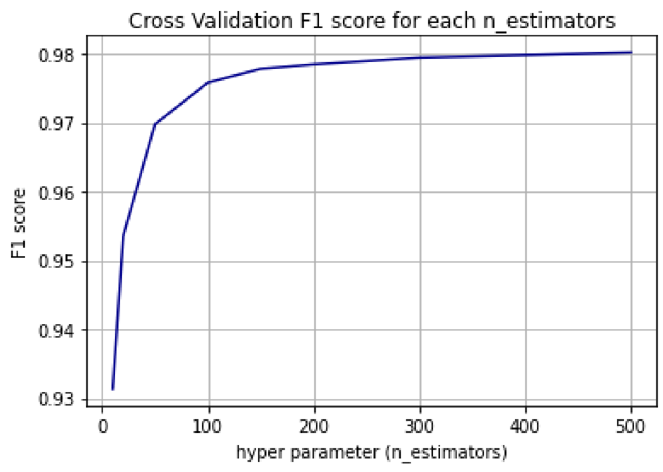
- RandomForest is bagging method, that means it has overfitted Decision trees as base learners. But ensembling overfitting will reduce.
- Since decision tree is overfitting in this situation, let us try with RandomForest with random Oversampling

RF

In [75]:

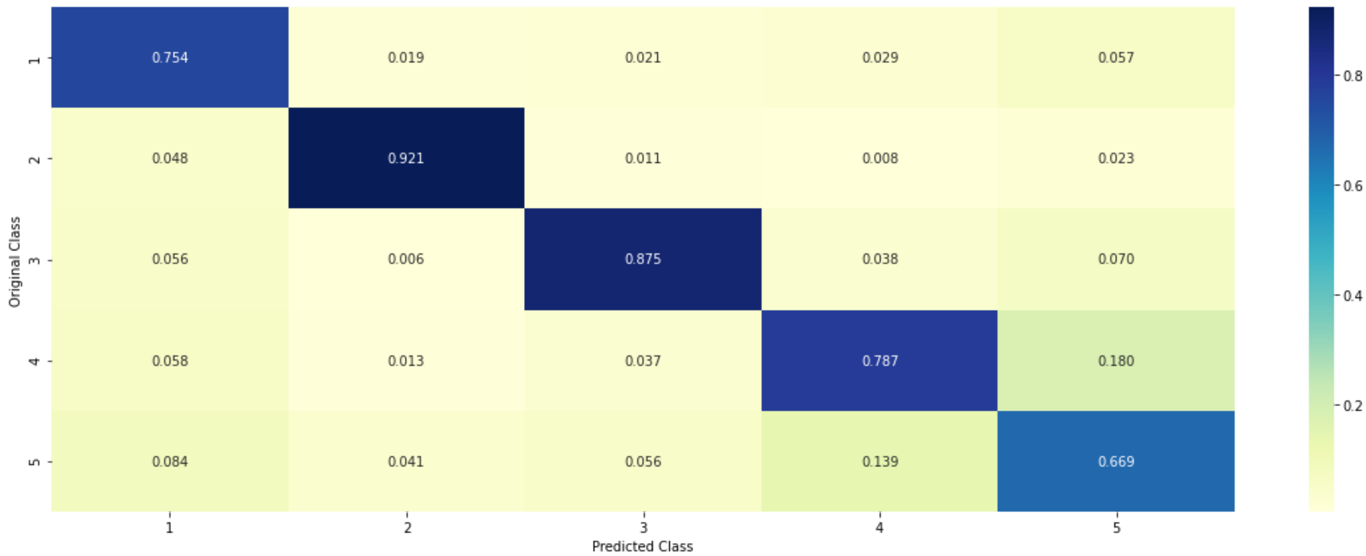
```
n_estimators=[10,20,50,100,150,200,300,500]


f1_scores = []
for i in n_estimators:
    model = None
    model = RandomForestClassifier(n_estimators=i)
    k_fold_score = kfold_sampling(5,model)
    f1_scores.append(k_fold_score)
    print("Macro F1 score at n={} is {} ".format(i,k_fold_score))



print("*"*50)
plt.plot(n_estimators,f1_scores,color="darkblue")

plt.grid()
plt.title("Cross Validation F1 score for each n_estimators")
plt.xlabel("hyper parameter (n_estimators)")
plt.ylabel("F1 score")
plt.show()

best_param = n_estimators[np.argmax(f1_scores)]

model = None
model = RandomForestClassifier(n_estimators=best_param)
model.fit(x_res,y_res)


print("*"*50)
print("Train F1 score at {} is :{}".format(best_param, f1_score(y_res,model.predict(x_res),labels=model.cl
print("*"*50)
print("test F1 score at {} is :{}".format(best_param, f1_score(y_test,model.predict(test_features),labels=


#plotting confusion matrix
predicted = model.predict(test_features)
plot_confusion_matrix(y_test,predicted)
```

```
Macro F1 score at n=10 is 0.9313607423429751
Macro F1 score at n=20 is 0.9535549871158185
Macro F1 score at n=50 is 0.9697554781509881
Macro F1 score at n=100 is 0.975800176793355
Macro F1 score at n=150 is 0.9778040758575797
Macro F1 score at n=200 is 0.9784423486493914
Macro F1 score at n=300 is 0.9794255424476516
Macro F1 score at n=500 is 0.9801736967596921
**************************************************
```

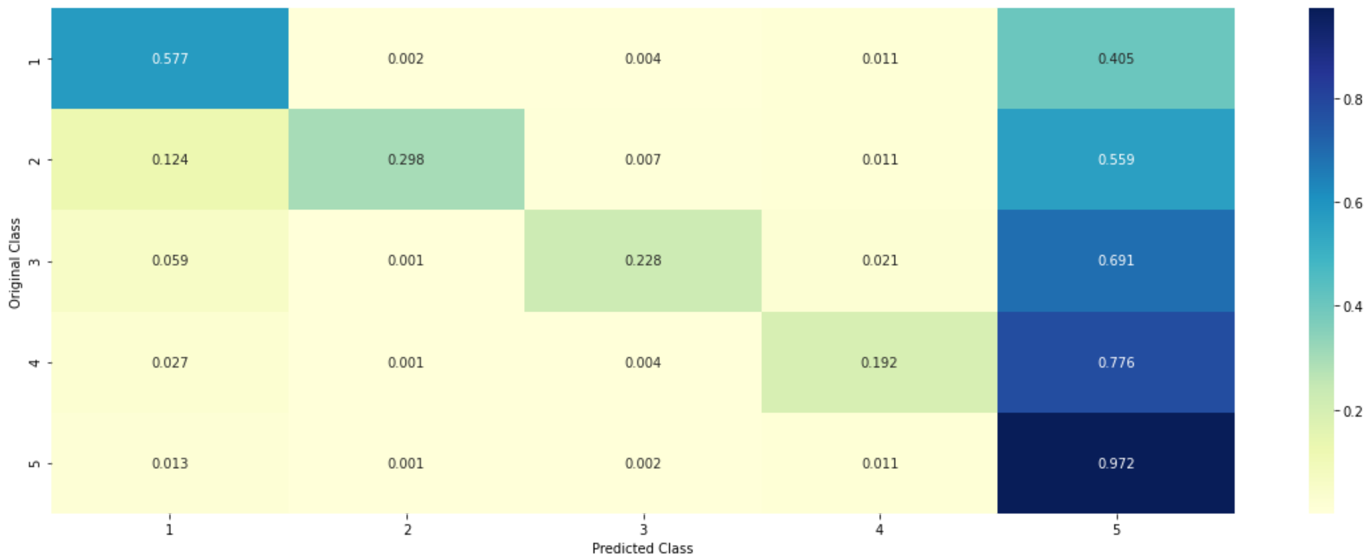



```
**************************************************
Train F1 score at 500 is :0.9985973924070967
**************************************************
test F1 score at 500 is :0.5136173216792821
-------------------- Confusion matrix --------------------
```


```
------------------- Precision matrix (Columm Sum=1) -------------------
```




```
------------------- Recall matrix (Row sum=1) -------------------
```



- But the model is overfitting

XGBRF model

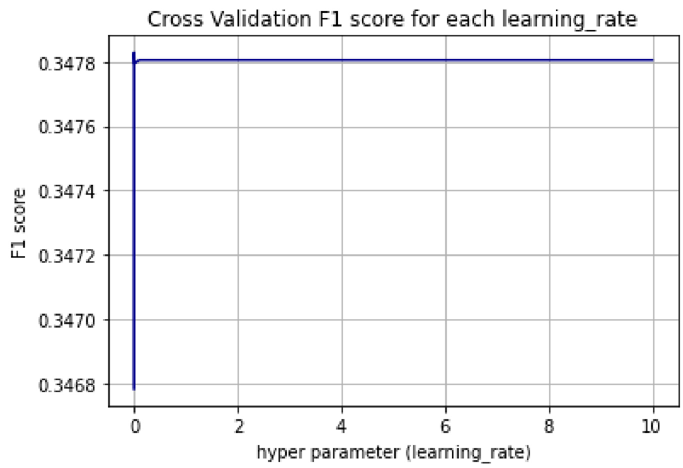
In [76]:
```
learning_rate=[0.00001,0.0001,0.001,0.01,0.1,1,10]

f1_scores = []
for i in learning_rate:
    model = None
    model = xgb.XGBRFClassifier(learning_rate=i)
    k_fold_score = kfold_sampling(5,model)
    f1_scores.append(k_fold_score)
    print("Macro F1 score at learning_rate={} is {} ".format(i,k_fold_score))



print("*"*50)
plt.plot(learning_rate,f1_scores,color="darkblue")

plt.grid()
plt.title("Cross Validation F1 score for each learning_rate")
plt.xlabel("hyper parameter (learning_rate)")
plt.ylabel("F1 score")
plt.show()

best_n = learning_rate[np.argmax(f1_scores)]


model = None
model = xgb.XGBRFClassifier(learning_rate=best_n,class_weight='balanced')
model.fit(x_res,y_res)


print("*"*50)
print("Train F1 score at {} is  :{} ".format(best_n, f1_score(y_res,model.predict(x_res),labels=model.clas
print("*"*50)
print("test F1 score at {} is :{} ".format(best_n, f1_score(y_test,model.predict(test_features),labels=moc


#plotting confusion matrix

predicted = model.predict(test_features)
plot_confusion_matrix(y_test,predicted)
```

```
[21:11:39] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[21:12:50] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[21:14:01] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[21:15:12] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[21:16:23] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
Macro F1 score at learning_rate=1e-05 is 0.34678451268527083
[21:17:34] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[21:18:45] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[21:19:57] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[21:21:09] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
```

```
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[21:22:22] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
Macro F1 score at learning_rate=0.0001 is 0.3470054714815595
[21:23:34] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[21:24:48] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[21:26:00] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[21:27:14] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[21:28:25] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
Macro F1 score at learning_rate=0.001 is 0.34782871658391057
[21:29:37] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[21:30:50] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[21:32:02] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[21:33:15] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[21:34:28] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
Macro F1 score at learning_rate=0.01 is 0.34779446844285794
[21:35:46] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[21:37:00] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[21:38:13] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[21:40:06] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
[21:42:12] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
Macro F1 score at learning_rate=0.1 is 0.3478055856922234
[21:44:24] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
```

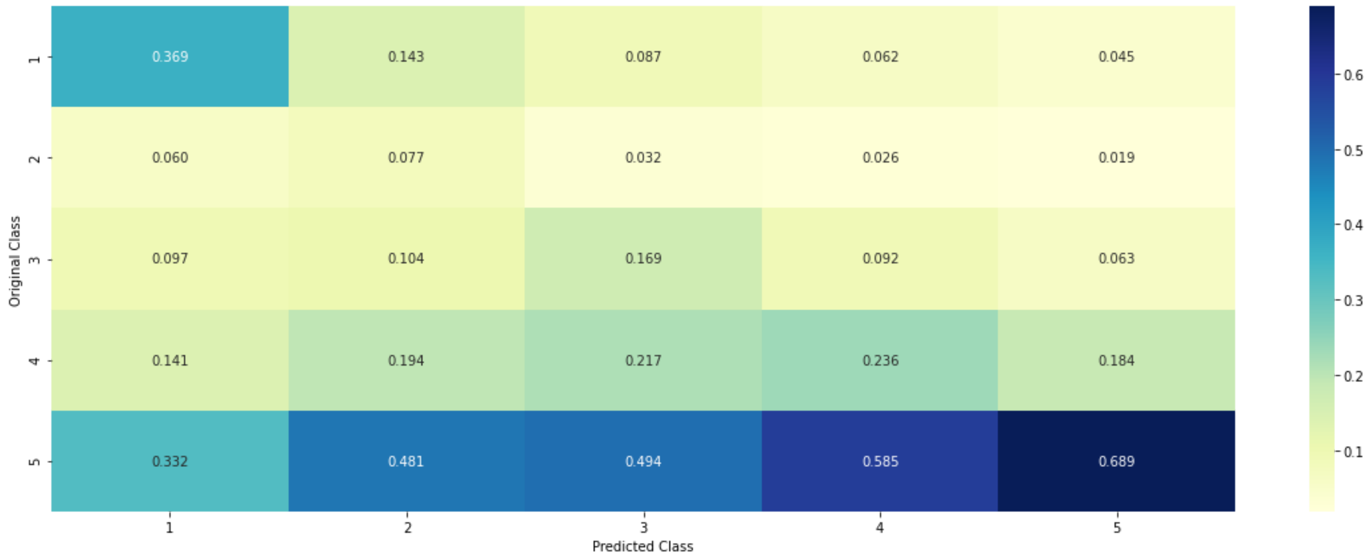
```
[21:46:49] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: St
arting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was chan
```

```
ged from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[21:49:19] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: St
arting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was chan
ged from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[21:51:51] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: St
arting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was chan
ged from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[21:54:23] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: St
arting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was chan
ged from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
Macro F1 score at learning_rate=1 is 0.3478055856922234
[21:56:55] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: St
arting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was chan
ged from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[21:59:28] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: St
arting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was chan
ged from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:01:30] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: St
arting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was chan
ged from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:03:28] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: St
arting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was chan
ged from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:05:28] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: St
arting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was chan
ged from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
Macro F1 score at learning_rate=10 is 0.3478055856922234
**************************************************
```

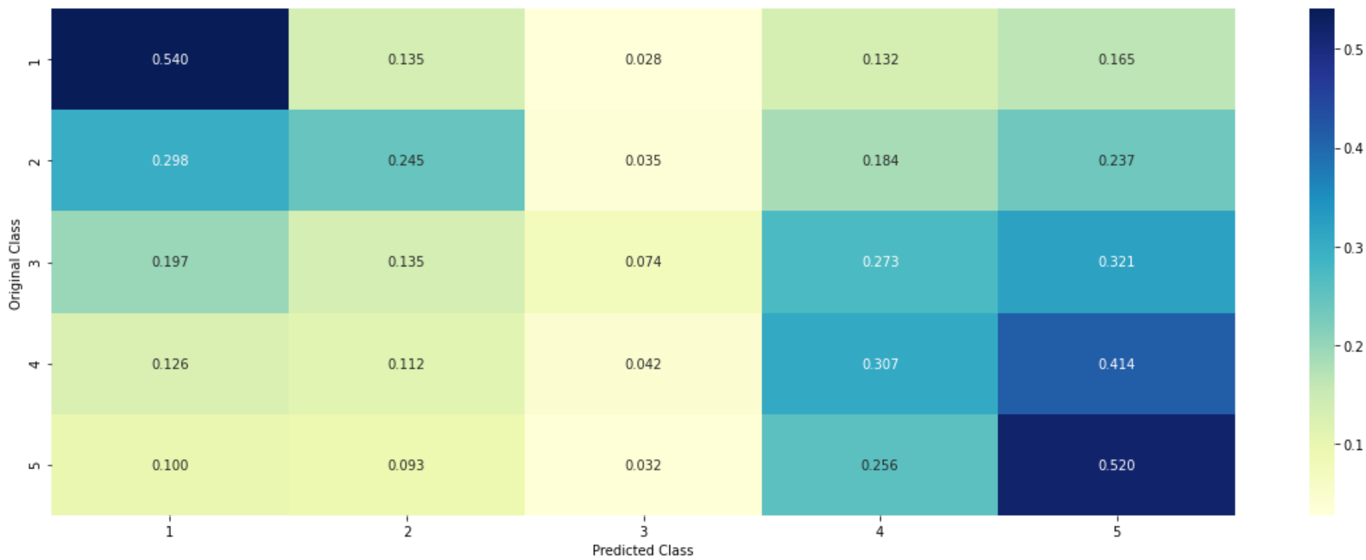



```
[22:05:30] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:541:
Parameters: { class_weight } might not be used.

  This may not be accurate due to some parameters are only used in language bindings but
  passed down to XGBoost core.  Or some parameters are not used but slip through this
  verification. Please open an issue if you find above cases.


[22:07:41] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: St
arting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was chan
ged from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
**************************************************
Train F1 score at 0.001 is  :0.35404401698400156
**************************************************
test F1 score at 0.001 is :0.30375644020951065
-------------------- Confusion matrix --------------------
```

------------------- Precision matrix (Columm Sum=1) -------------------



------------------- Recall matrix (Row sum=1) -------------------



In [ ]:

In [ ]:

1.4.3. LGBM

In [71]:
```
param_grid = {
    'learning_rate': [0.001, 0.01, 0.1, 0.2],
    'n_estimators': [5,10,50,100,200,250]}

clf = lgb.LGBMClassifier(n_jobs=-1,boosting_type="goss")
random_search = RandomizedSearchCV(clf, param_grid, n_iter=30,n_jobs=-1,scoring="f1_macro",
                                   verbose=1, cv=5, refit=False, random_state=42)
random_search.fit(x_res, y_res)
```

```
Fitting 5 folds for each of 24 candidates, totalling 120 fits
```

Out[71]:
```
RandomizedSearchCV(cv=5, estimator=LGBMClassifier(boosting_type='goss'),
                   n_iter=30, n_jobs=-1,
                   param_distributions={'learning_rate': [0.001, 0.01, 0.1,
                                                          0.2],
                                        'n_estimators': [5, 10, 50, 100, 200,
                                                         250]},
                   random_state=42, refit=False, scoring='f1_macro', verbose=1)
```

In [72]:
```
params = random_search.best_params_
```

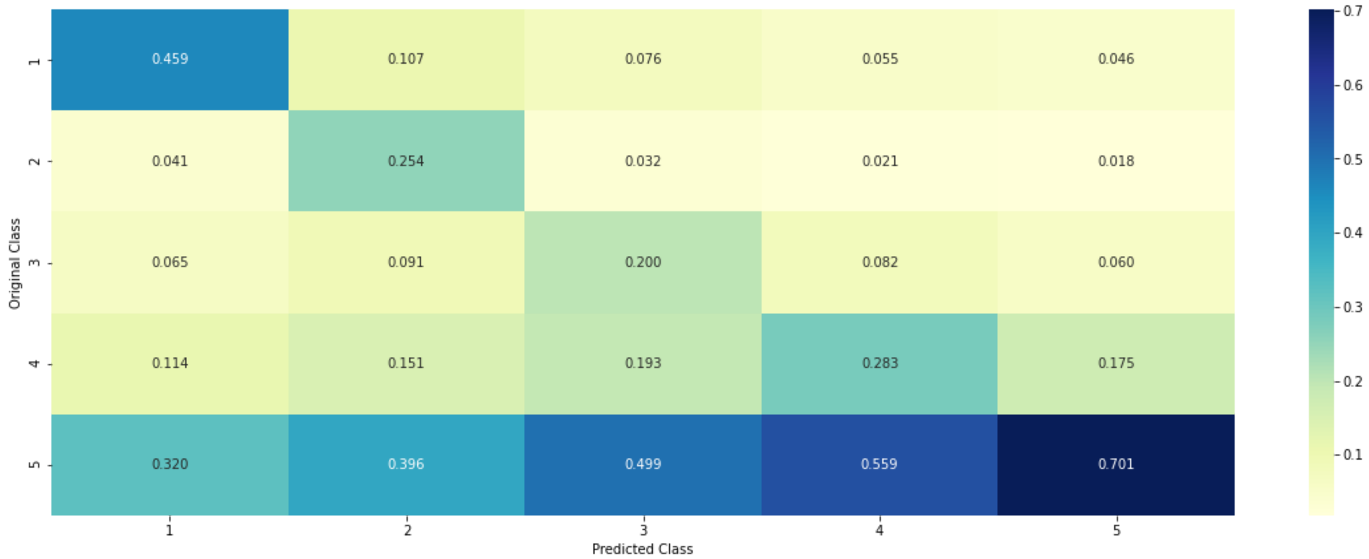
In [73]:
```
print(params)
```

```
{'n_estimators': 250, 'learning_rate': 0.1}
```

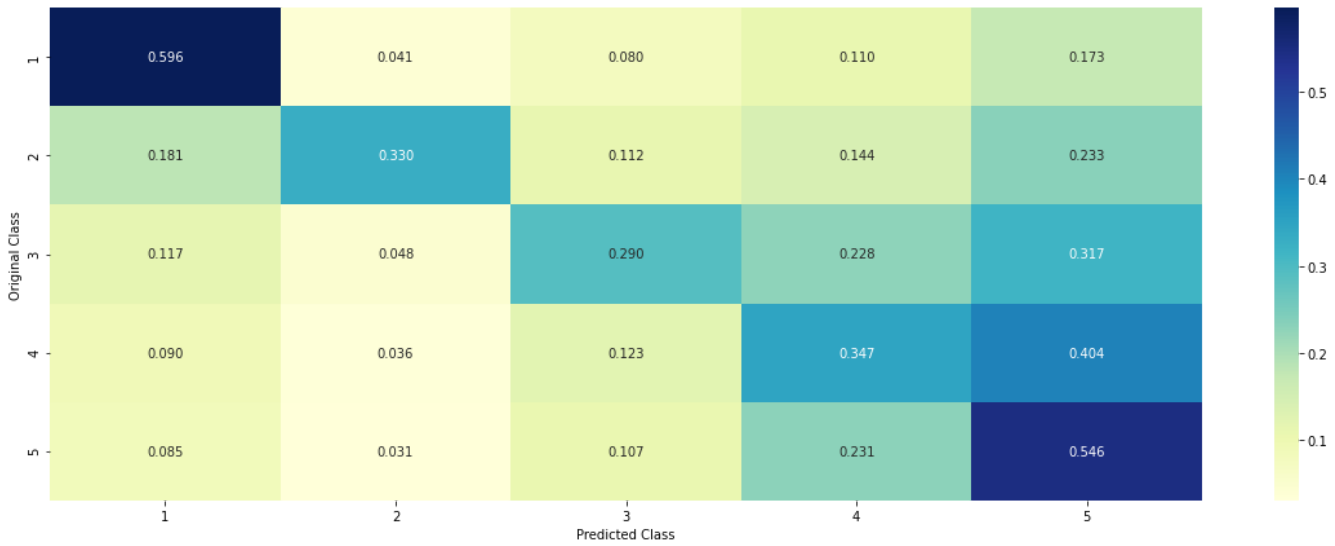
In [74]:
```python
clf = lgb.LGBMClassifier(n_estimators= params["n_estimators"],
                         boosting_type="goss",
                        learning_rate= params["learning_rate"], n_jobs=-1)
clf.fit(x_res,y_res)

pred_test = clf.predict(test_features)
pred_train = clf.predict(x_res)

print("Train F1 score is  :{} ".format(f1_score(y_res,pred_train,labels=[1,2,3,4,5],average="macro")))
print("*"*50)
print("test F1 score is :{} ".format(f1_score(y_test,pred_test,labels=[1,2,3,4,5],average="macro")))

plot_confusion_matrix(y_test,pred_test)
```

```
Train F1 score is  :0.7637536506482032
**************************************************
test F1 score is :0.39361553077802675
-------------------- Confusion matrix --------------------
```


```
-------------------- Precision matrix (Columm Sum=1) --------------------
```




```
-------------------- Recall matrix (Row sum=1) --------------------
```



- **Test macro F1 score is not imrpoved. But main observation here is the model gave some importance to minority classes. And recall of class 1 is 60%, class 2 is 33%, class 3 is 29%. This is little bit improvemtn.**
- **Also Precision of class 5 is 70%.**

- With oversampling, result has not improved incase of LGBM
- Still model is suffering from misclassification error.

In [ ]:

Summary Table

We have performed 5-fold cross validation for all models.

```
In some models difference between test and train macro F1 score is high, in some models this diff
erence is low.
We have not get high macro F1 score for any model.
```

With original data

Model	Test Macro_F1 score	Train Macro_F1 score
Logistic Regression	0.284	0.286
KNN	0.35	0.64
Decision Tree	0.32	0.44
Random Forest	0.433	0.993
Light GBM with goss	0.51	0.98
Light GBM with goss+ fine tuning	0.46	0.99
XGBRFBoost	0.239	0.249
XGBoost	0.359	0.539

With Random Oversampling

Model	Test Macro_F1 score	Train Macro_F1 score
Logistic Regression	0.28	0.30
Decision Tree	0.38	0.70
Random Forest	0.51	0.99
XGBRF	0.30	0.35
Light GBM	0.39	0.76

- We can see that result has not improved with RandomOverSampling.
- LightGBM with goss boosting type is the model which gave better result compared to all other models with macro F1 score 0.513.

In [ ]:

```

```